Hunger Games:
Analyzing Relationships between Food Insecurity and Violence

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Abstract

What impact does food security have on patterns of conflict within developing states? Does increasing local food security levels exacerbate or help to quell violence in these areas? Answering these questions using both high-resolution and global data on conflict and food production, as well as a large variety of analytical techniques designed to address the different reciprocal and sequential relationships between food production and conflict, my dissertation shows that—contrary to previous expectations—conflict in the developing world is frequently driven, on average, by abundance and not by scarcity.

The dissertation establishes two mechanisms to explain this relationship. The first involves conflict designed to secure local food resources for the group's own consumption, and is hence termed "possessive conflict" over food security. The second relates to situations where armed groups use violence to regulate the food supply available to other groups by preventing access to and destroying these resources, and is hence termed "preemptive conflict" over food security.

Original archival evidence from the Mau Mau rebellion in Kenya highlights the microlevel importance of controlling food resources and increasing group—and community—resilience; different armed actors might therefore gravitate into food-abundant areas, increasing the frequency of local armed conflict and incidents of violence against civilians. This archival evidence also shows that some food resources, such as maize and wheat, are much more valuable as an input of rebellion, and are thus more likely to and more frequently attract conflict locally.

Finally, the role of highly nutritional food resources in engendering and perpetuating rebellions is evaluated on a global sample consisting of all rebellions. The data used in these macrolevel cross-national models builds on food types and other factors deemed especially salient in the microlevel analyses. Substantively, the effect of nutritious food resources is shown to surpass that of other benchmark explanations of conflict such as economic development and political openness. These findings suggest that food resources and their impact on rebellions should be taken seriously by academics and policymakers alike.

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Chapter 1: Introduction

Motivation

Despite Napoleon's famous maxim that, "the army marches on its stomach," conflict scholars rarely if ever consider the imperative to secure food resources for military operations in their theories. Research on rebellions—civil and anti-colonial wars—frequently emphasizes issues related to the distribution of natural resources (Collier and Hoeffler, 1998; Blattman and Miguel, 2010; Buhaug, Gates and Lujala, 2009; Deiwiks, Cederman and Gleditsch, 2012). Yet, this perspective focuses specifically on lucrative resources such as oil, drugs, or diamonds (Collier and Hoeffler, 1998; Wood, 2010; Weinstein, 2007) that are very rare, or completely absent from many conflict-afflicted countries. As a result, later research questioned the importance of some profitable resources in generating rebellions (Ross, 2004*a*). Food, in contrast, is a necessary input of rebellion. While rebel groups *can* operate without these rare resources, they *must* guarantee access to food. Because food is a necessary input, research on conflict largely treats it as constant: groups must secure food in every rebellion, therefore it should not be treated as a variable in conflict analysis, especially as proxies such as population densities or geospatial features already capture some factors affecting food access (Fearon and Laitin, 2003; Buhaug, Gates and Lujala, 2009).

In this dissertation, I advocate a different perspective. I argue that securing food supplies is more challenging than previously thought. I further claim and show that different types of food support exist, and that the variation between the food types accessible to armed groups has a strong impact not only on the group's ability to physically feed its troops, but also on the latter's fighting capability and morale. Groups that can access more nutritious food can feed more troops, and can also guarantee that these troops' morale levels are high, which helps the group to motivate its members to fight toward a common goal. Therefore, more access to local food resources—especially nutritious, durable staple crops—explains more variation in the onset, conduct, and outcome of violent conflict than is currently appreciated.

This perspective centers on the fighting capacity of armed groups, rather than governments or states, which have been the tenet of some previous prominent studies. Fearon and Laitin, for instance, test a large number of potential inputs of conflict, and conclude that "financially, organizationally, and politically weak central governments render insurgency more feasible and attractive due to weak local policing or inept and corrupt counterinsurgency practices" (2003, 75-76). While this is an insightful finding, it is focused on how regime-centric attributes influence conflict, rather than what inputs are especially important for the groups themselves. Local food availability is such an input. For example, a close look at data on total annual production of maize—one of the most important and prevalent staple crops grown worldwide (Food and Agricultural Organization of the United Nations, 2013; Oerke and Dehne, 2004)—by country, which are used in the macrolevel analysis presented in Chapter 4, shows that it *positively* and considerably correlates ($r = 0.227$) with the number of years that these countries experienced rebellions over the Cold War (specifically, 1961–1988) period. For comparison, over the same period, GDP per capita, a widely-used measure of state capacity and a strong predictor of a rebellion in Fearon and Laitin (2003),[1] shows practically no correlation, with $r = 0.078$ value.

Qualitative evidence further supports the importance of the role food plays in conflict, as suggested by these quantitative correlations. For instance, Weinstein finds that a crucial aspect of the National Resistance Army's (NRA) success in Uganda was its ability to effectively organize food contribution from the local population (2007, 175-180). This allowed the NRA to provide credible commitment to both rebels and civilians, a system that "reduced the potential for corruption and ensured that the demand for food was not unmanageable" (2007, 179). From a complementary perspective, research into the motivations of armies to use a "scorched earth" policy during insurgencies found that states frequently use these tactics to thwart the ability of rebels to obtain food supplies from the local population, as happened, for instance, in Guatemala and Eritrea (Valentino, Huth and Balch-Lindsay, 2004; Downes, 2008; Valentino, 2004). Even less violent campaigns that do not involve mass killing still rely on efforts to limit the ability of rebels to access food resources by better guarding these resources and relocating populations that might provide food to the rebels, as happened, for instance, in Malaya (Ramakrishna, 2002) and Uganda (Doom and Vlassenroot, 1999).

The cross-national and anecdotal evidence reported above suggests the existence of an important pattern of conflict, while the relative rarity of research on linkages between food and civil war highlights the need for a more systematic anal-

[1] Referred to as "income per capita" (Fearon and Laitin, 2003, 83).

ysis of these features. Why do armed conflicts, civil wars, and rebellions occur and persist in some countries but not in others? What impact do food resources have on local and global conflict patterns? In this dissertation, I develop a theory that answers both questions. The need to sustain a continuous supply of food is perhaps the most acute aspect of deficiency in logistic support available to both rebel groups and—frequently—state forces. I suggest that overcoming these deficiencies and, moreover, securing wide access to *nutritious* food resources will have a strong and positive impact, both on the organization's strength and its troops' morale. Regular access to food also allows groups to overcome collective action problems by providing troops with credible commitment to fight a long war. Troops who know they will be supported are more motivated to fight (Weinstein, 2007, 174-175; 178-179).

While securing regular access to food resources is a crucial aspect of warfare in the developing world, the effect of food on conflict begins at the most fundamental level, with the behavior of troops, atrocity perpetrators, and even innocent civilians. As I show in Chapters 2 and 3, locally, food resources generate a large number of social conflicts, many of which are not part of the standard rebel vs. government logic; communities living in rural areas where they subside on food sourced locally must frequently use violence to guarantee their survival. In Chapter 4, I also show that food resources also have a strong effect on the likelihood of rebellions—such as civil and anti colonial wars and coups d'etat—and conflict duration, much more so than previously thought. These are the central empirical finding presented in this dissertation, and a novel contribution to the growing literature in political science, economics, geography, and environmental science on relationships between the environment, climate, and war. This dissertation, however, provides much more than just establishing these relationships. It explores different mechanisms linking food abundance and violence at both the micro- and macrolevels, and provides new theoretical frameworks and data to stimulate future research on these issues. In doing so, it also highlights possible means and useful strategies of conflict mitigation.

Food and Rebellion: Concepts and Theory

In this section, I posit a theory that links (i) access to food resources as a crucial aspect of warfare with, (ii) armed groups' strategic behavior during conflict. At the heart of this theory is the imperative to secure food supplies, a critical input for warfare. Unlike profit-generating natural resources such as oil and diamonds, which do not exist in many rebellion-afflicted countries and regions, food is necessary for all rebel groups to operate. Even if the group has many motivated recruits willing to fight, without being able to feed these troops, it cannot wage and sustain a long conflict. Moreover, I further claim that the group's ability to provide its troops with regular access to *nutritious and durable* food resources has a strong positive effect on the troops' morale, making them more willing and able to fight a long rebellion, thus allowing military and rebel leaders to induce compliance from group members.[2]

The term "food security" as used in this dissertation thus refers to the ability of groups, households and individuals to secure adequate levels of food resources

[2] In the theory of warfare, specifically, developed here, whether food is obtained using coercion or enticement is not pertinent, because the model is agnostic with respect to apportionment dynamics as highlighted by, e.g., Kalyvas (2006); Wood (2003). Nevertheless, as discussed in the next section, the focus on food abundance has some important implications for research on the causes of civilian victimization.

for self sustenance (Barrett, 2010; Hendrix and Brinkman, 2013). Correspondingly, "food insecurity" refers to situations where food security levels are low, inadequate, or unstable, and thus highly susceptible to negative shocks caused by environmental and political conditions. In these contexts, the amount of food resources required to guarantee sufficient dietary intake for all individuals in the region might decrease as a result distributional limitations or production shortages (Barrett, 2010). Empirically, this dissertation analyzes variations in food resources, staple crop yields, and food production to approximate food security and its effect on different warring groups. These concepts are applied to derive a better understanding of the strategic motivations of armed actors, and how these motivations are influenced by variation in food production and resources availability. This theoretical framework allows me to construct explanations for violent conflict that draw on terms and concepts from the food security literature. These frameworks also mean that the food production indicators used here are derived based on specific theoretical expectations. These indicators are hence good proxies for the specific aspects of food security I seek to empirically capture in the different analyses of local and global conflicts conducted in this dissertation. Importantly, while the specific mechanisms at play are validated on high-resolution data for Africa as the world region most susceptible to the effects of climate change and food insecurity (Food and Agriculture Organization of the United Nations, 2008; Burke et al., 2009), these microlevel findings are validated on a global sample in the cross-national macrolevel analysis presented in Chapter 4.

As the reader will be repeatedly reminded in the ensuing chapters, when food is discussed in the context of conflict in current research, the emphasis is usually on the *labor* aspect of food security. Decreases in agricultural output are associated with more labor flexibility, which results in cheaper labor and more recruits being available to rebels. This approach thus equates conflict with an oversupply of labor. This is a reasonable argument, and there are several reasons to assume that it is valid.

First, numerous studies established that lower economic development is a quite robust indicator of civil war (e.g., Hegre and Sambanis, 2006; Fearon and Laitin, 2003; Blattman and Miguel, 2010). The largest sector in most civil war-afflicted economies is agriculture (De Soysa et al., 1999). As a result, diminishing agricultural output substantively shrinks the economy, and hence leads to more civil war (Miguel, Satyanath and Sergenti, 2004; Burke et al., 2009).

Second, lower economic returns in the labor-intensive agricultural sector, often followed by rising unemployment and lower wages in primarily rural economies, facilitate rebel recruitment and strengthen civilian support for rebel movements. Fjelde (2015), for instance, shows that negative changes to the value of local agricultural output, which combines sub-national crop production maps and data on movements in global agricultural prices, substantially increase the risk of violent events, presumably as more unemployed labor is available for recruitment.

Third, local shrinkages in food production in countries and regions already afflicted by conflict are unlikely to be addressed via affective state-level interventions and smoothing mechanisms. As Wischnath and Buhaug (2014) argue, in the absence of alternative modes of living, people living off the land are forced to pursue unconventional coping strategies when drought strikes or other environmental conditions severely impact agricultural production. Facing insecure revenue from agriculture lowers the opportunity cost of joining an ongoing conflict (as well as criminal behavior and looting more generally). Under these conditions, violent action emerges as a tempting alternative source of income to sustain one's life and livelihood.

Despite these important insights, however, the focus on food scarcities alone falls short of explaining why, as shown below, conflict frequently show a *positive* association with food resources (see, also, e.g., Koren and Bagozzi, 2016; Crost and Felter, 2016). After all, having a higher number of potential recruits at the rebel group's disposal means little if the group cannot be certain that these recruits will become good and effective rebels, let alone be able to physically support them. Moreover, from an empirical perspective, an important feature of many of these scarcity-centric explanations is that the data used to support them is frequently measured at the country or, at best, state/province level (see, e.g., Burke et al., 2009; Miguel, Satyanath and Sergenti, 2004; Buhaug, 2010; Wischnath and Buhaug, 2014). Even studies that rely on a higher levels of disaggregation, such as the 0.5○ x 0.5○ grid level, almost exclusively rely on *static* and *general* measures of cropland as "green" areas (e.g., Koren and Bagozzi, 2016; O'Loughlin et al., 2012), or attempted to coerce such constant measures into being time-varying via extrapolation, using, for example, global food price (e.g., Fjelde, 2015; Hendrix and Haggard, 2015).

A I show throughout this dissertation, these empirical choices have important implications. Indeed, a close examination of data at higher levels of disaggregation or information on crops that does vary over time suggest a different trend, which does not support the scarcity-centric argument. For instance, Figure 1.1 plots the area affected by civil war (operationalized as the number of affected 0.5○ x 0.5○ grid cells, or squares of approximately 55km x 55km, which decrease in size as one moves toward the Poles) with at least 25 combatant casualties (Tollefsen et al., 2012), against the total annual level of wheat yields (operationalized as average, *yearly* yield levels by 0.5○ x 0.5○ grid cell) (Ray et al., 2012)[3] in Eastern Africa, the world region most heavily analyzed by studies of the climate-conflict nexus (e.g., O'Loughlin et al., 2012; Maystadt and Ecker, 2014; Adano et al., 2012; Raleigh and Kniveton, 2012). Moreover, Figure 1.2 additionally correlates the average levels of *staple food crops*, specifically, in Africa,[4] with the total frequency of conflict events by 0.5○ x 0.5○ grid cell for 1998-2008 as measured by the Armed Conflict Event and Location Version 6 Dataset (Raleigh et al., 2010), with 95% confidence intervals.

As both figures show, at the highly localized level, food crops productivity exhibits a *positive* and relatively strong (when observational data are concerned) correlation with conflict frequency within the world region most closely associated with scarcity. These correlations might simply be coincidental, but I argue that they are evidence of a broader trend, which requires different micro- and macrolevel approaches to understanding the relationship between food and conflict.

An alternative perspective is thus to look at food as a valuable, and indeed a crucial, natural resource, used to satisfy armed groups' demand for effective and dependable troops. This perspective builds on research into the impact of profitable natural resources on conflict. For instance, Collier and Hoeffler argue that, "the incentive for rebellion conditional upon victory, is determined by the capacity of a future rebel government to reward its supporters" (1998, 564). Indeed, the idea that access to natural resources influences rebel groups' strength and strategic behavior is firmly established in the extant literature (e.g., Hazen, 2013; Collier

[3]A more detailed discussion of this variable is provided in Chapter 2.

[4]Measured at the highly disaggregated 0.08○ x 0.08○ level, or 1km x 1km at the equator for the year 2000, and averaged to the 0.5○ x 0.5○ level.

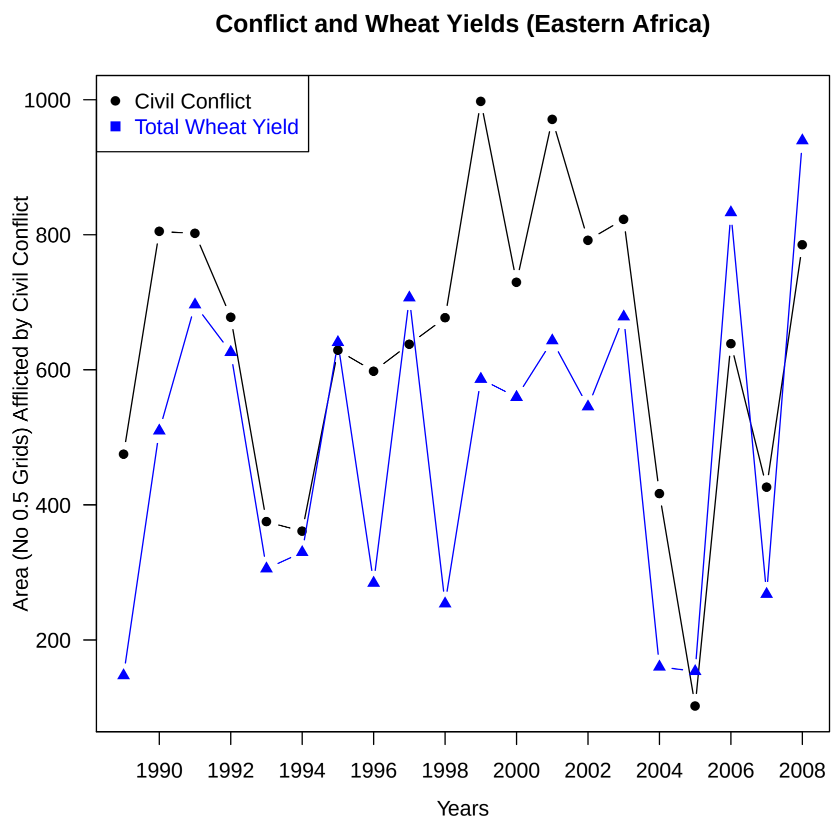


Figure 1.1: Civil War and Wheat Yields in Eastern Africa

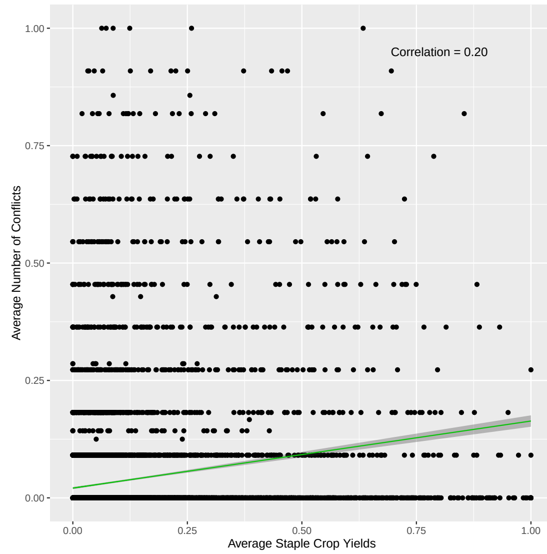


Figure 1.2: Conflict and Staple Food Crops (% of 0.5○ Grid Cell Coverage) in Africa

and Hoeffler, 1998; Wood, 2010). Previous studies linked natural resources to conflict through pathways such as perceived economic injustice (Deiwiks, Cederman and Gleditsch, 2012) and limitations on access (Hazen, 2013), and argued that organizational capacities interact with geographic factors to maximize these groups' ability to fight long conflicts (Buhaug, Gates and Lujala, 2009). Access to these resources improves the group's capacity to recruit and support more individuals, although in doing so leaders might also risk attracting opportunistic, undependable volunteers (Weinstein, 2005).

A key natural resource, yet one that is practically absent from many of these studies, is food. If, as Collier and Hoeffler (1998) argue, the incentive for rebellion is conditional on the probability of victory, then higher access to nutritious food is practically a prerequisite for victory. Moreover, profitable resources such as oil or diamonds are not present in a large number of rebellion cases. For instance, within the state-level sample analyzed in Chapter 4, of the 64 countries that experienced rebellion, 31 did not have any level of, or no information was available on, oil production. Food resources, in contrast, represent a different category.

For example, in their study of relationships between food and conflict in the Sahel, Hendrix and Brinkman state that, "[r]ebel movements typically do not grow their own food and depend on voluntary or coerced contributions from the population" (2013, 4). Somewhat more nebulously, Messer claims that "[t]he exact sequence by which food insecurity contributes to conflict tends to involve complex factors, including environmental scarcities and identity-based competition for access to and control over what are perceived to be limited resources. These factors combine to deepen a sense of unjust deprivation and unfairness" (2009, 18). Indeed, food is even more important than other natural resources for different warring factions in developing countries, where logistic support is a rarity, and frequently does not exist, meaning that forces must rely on food sourced locally for survival (Kress, 2002; Koren and Bagozzi, 2016; Henk and Rupiya, 2001). The amount of potential recruits available, a key aspect emphasized in previous studies (e.g., Fjelde, 2015; Burke et al., 2009; Wischnath and Buhaug, 2014), is irrelevant if a group lacks the ability to actively recruit and support these individuals. From this perspective, food abundance corresponds to the availability of ample capital in regions where measures such as economic production do not adequately capture true microeconomic incentives or means of wealth.

Broadly, at least three factors distinguish food from other natural resources. First, food is a *compulsory* resource. Without food, armies cannot march and insurgents cannot recruit. Wars cannot be won if access to locally produced food resources does not exist and persist (Weinstein, 2007). Nor—as I show in Chapters

2 and 3—can rebellions be easily quashed if rebel groups can guarantee and protect local food support points that allow these organizations to operate in different regions for long periods of time. Sufficient access to locally sourced food is thus crucial in facilitating the success of a an armed group, even in the case of more durable foods; the ability of different armed actors to control key food provision points is paramount. This was recognized by the NRA in Uganda, which aimed to establish committees in areas of relative food abundance, to guarantee regular flow of those resources to its members (Weinstein, 2007, 174-175). Similarly, in eastern India, Communist Naxiliate rebels operate primarily in the agricultural districts of Chattisgarh, especially Bastar and Dantewada, where rice fields are predominant (Singh, 2006). And in Iraq, "[t]he jihadist manual *The Management of Savagery* (idarat al-tawahhush) that has a cult following among ISIS supporters identifies access to territories with food production as vital for control of conquered areas" (Jaafar and Woertz, 2016, 15).

Second, because food is necessary and compulsory, it is also *agnostic*; the need to obtain regular food support as a mobile group outweighs whatever particular motivations, food-related or otherwise, that led a group member to join the group. Granted, as with other profitable resources, in different regions, civilians might cite various incentives for joining or supporting different sides, or fighting against them. In some places, potential recruits might be motivated by "grievances," for example, if the government's response to famine is politicized and relief funds are diverted. For instance, Hendrix and Brinkman (2013) claim that, in the Sahel, "food insecurity can be a source of grievances that motivate participation in rebellion" (2013, 2). In other locations, participation might be motivated by "greed," for example because recruits seek to consolidate control over a larger share of agricultural resources, especially if prices of these resources increase significantly due to conflict (Crost and Felter, 2016). Nevertheless, once an individual has joined the group, his or her motivations with respect to food matter less compared with the need to be fed regularly while participating, which often involves frequently moving from place to place. This differentiates food from other natural resources. In the latter case, as Weinstein argues, "resource-rich rebel groups are overwhelmed by opportunistic joiners" (2005, 605), who share no commitment to the group's aims and joined simply to make a profit. In the case of food, however, the original payoff is not as high (say, a bag of rice vs. revenue from oil or diamonds), and might not even offset the opportunity costs of joining, while the value of food *after* a recruit joins increases substantially due to the fact that these groups are mobile rather than stationary (Koren and Bagozzi, 2016; Mkandawire, 2002). Eating on a regular basis is vital, regardless of the value of food outside the group's context, and even more so because groups are frequently unable to grow their own food due to their mobile nature.

Finally, because food is a compulsory and agnostic resource, it is also *binding*. Individuals who join the group and fight an ongoing conflict must do what is expected in order to be fed. Correspondingly, if the troops are not fed, then their social contract with the group as a whole is undermined. Thus, in addition to its impact on physical performance, food access has a *psychological* effect on bringing group members closer together and increasing their fighting morale. For instance, the Holy Spirit Movement in Uganda, a precursor of the Lord's Resistance Army (LRA), emphasized the role of food as an instrument of group building, instructing its troops that "you shall not eat food with anybody who has not been sworn in by the Holy Spirit" (Doom and Vlassenroot, 1999, 18). Indeed, as Boring writes in his study of American troops during the Second World War, physically, for experienced troops, "pride in the ability to keep going on little, plus realization of the military necessity of so doing, offsets in considerable degree the tendency to a lowering morale" (1945, 328). At the same time, however, "[i]f the needs of troops for water and food are not satisfied, if they are thirsty and hungry, then morale goes down. Men tend to become irritable and jittery; they are likely to be aggressive and quarrelsome, projecting their troubles on others, finding fault where no fault lies " (1945, 327).

Thus, armed groups are expected to frequently move into—or actively fight over—areas where more food is accessible in order to *possess* these resources for consumption, and possibly to guarantee control over these areas for the long term. This allows group leaders to ensure their troops are well-fed, and thus an effective warriors who are bound together to fight toward a common goal. It also gives these commanders tools to credibly commit to their members that they can fight and win a long conflict. Because this behavior is concerned primarily with the necessity to secure food for personal consumption, I term it *possessive conflict* over food security. I discuss possessive conflict and its causes in great detail and empirically illustrate its validity at the highly-localized level in Chapter 2.

The salient role of nutritious food as a morale builder for armed troops, especially rebels, has not gone unnoticed by counterinsurgency operation commanders. For instance, the British colonial forces in Malaya (and, as described in great detail in Chapter 4, in Kenya), embarked on food denial campaigns, which involved relocating particular civilian populations that might provide food to the rebels, or harvesting crops in areas susceptible to rebel raids. This was done not only to limit the rebels' access to food supplies and keep the group's size small, but also to hurt rebel troops' morale. In such campaigns, "underlying the food denial concept was an innate appreciation of terrorist psychological vulnerabilities. Hence food denial was premised on creating 'cumulative pressures,' both mental and physical, over a period produced by privation, fear, and hopelessness" (Ramakrishna, 2002, 141).

Similarly, in Vietnam, during Operation Ranch Hand, the United States sprayed herbicides over large sections of South Vietnam and Laos, an effort done, in large part, to limit the availability of nutritious cereals accessible to the Viet Cong (Westing, 1972). In large part, this effort was "directed against rice and other crops as an important component of the US resource denial programme. Rice was the target for destruction in their first known herbicide attack in November of 1961, and rice was the target for destruction in the last US attack, prior to the suspension of direct US involvement in this manner in early May of 1971" (Westing, 1972, 322).

Like in Malaya, food denial efforts during the Vietnam campaign were intended to damage the Viet Cong's morale and fighting capability. For instance, the 1st Divisional Intelligence Unit of the Australian Task Force concluded in April 1970 that, "[t]he problems caused by hunger or starvation among [enemy] troops in the field, manifest themselves in almost every conceivable manner resulting ultimately in an almost complete breakdown in operational effectiveness" (Ross, Hall and Griffin, 2015, 241). And in Uganda, as part of the government's campaign against the LRA, "some 75,000 were forced to move into so-called 'protected villages,'" in a "classical counter-insurgency maneuver designed to deny rebels access to food by scorched-earth tactics" (Doom and Vlassenroot, 1999, 31). As these examples demonstrate, food binds the group members to each other, and helps to form the social contract underlying the group's very existence. Correspondingly, reducing the group's ability to regularly access nutritious food weakens these binds, and is hence a powerful counterinsurgency strategy.

These counterinsurgency strategies, while extreme, highlight a second linkage between food and violence, which relates to the necessity to regulate the amount of resources accessible to *other groups*. Moreover, such strategies should not necessarily involve extreme "scorched earth" policies, such as mass killing and the total destruction of resources; they can simply be focused on controlling specific food abundant focal points. I accordingly term this interaction *preemptive conflict* over food security, and discuss it in great detail and evaluate its validity empirically at the highly-localized level in Chapter 3. According to this logic, armed groups might initiate conflict in food abundant areas not (only) to possess these crucial food resources, but rather to prevent rival groups from gaining access to them. Like possessive conflict, these preemptive tactics do not have to take place solely between government and rebel groups. As shown in Table 3.1 in Chapter 3, militias representing different communities and ethnic groups are also likely to initiate conflict over cropland or pastureland to prevent rival groups from accessing these resources, rather than for the purpose of possessing them.

Taking a more holistic (i.e., less "grassroots" oriented) view on conflict, the three aforementioned aspects of food as a natural resource—that it is compulsory, agnostic, and binding—make it a crucial element of the group leadership's capacity to commit to its members, and vice versa. As illustrated in Chapter 4, which focuses on how food resources condition rebellions both locally and globally, the ability to show to its troops that they are fed and can expect to be fed as the rebellion progresses illustrates the group's credibility, and hence its ability to (i) fight a long conflict, and (ii) win it.

Moreover, this ability to provide ample food support can have long-term externalities in other areas that also increase the group's credibility. For instance, UNITA, a former Angolan rebel group, provided its members with levels of sustenance that were far more impressive than those allocated to government troops. By the end of the war, "[i]nsufficient food has lowered morale in many areas, principally among the more numerous government forces, some of whom sleep on the damp ground," while many UNITA rebels were able to, "live in impressively constructed grass thatched houses, retrieve water from a specially designed reservoir, and have built schools and health posts for their members" (Finkel, 1992, 62). A strong group can illustrate that its troops are able to work together toward a common goal as long as all group members (and ideally their families) are taken care of, which allows such groups to improve their internal cohesion and reduce the probability of "free-riding" among their members. Overall, these different features of food in rebellion suggest that conflict patterns should, on average, closely follow access to locally sourced food, with higher access at the local level and higher availability at the national level translating into more violence.

Contributions to Extant Research

Does the focus on food abundance offers new, relevant insights, or is it simply stating what was obvious to scholars and military leaders since prehistoric times? From an alternative perspective, does the emphasis on the role of food abundance simply sets up a "straw man," considering that war-prone countries also tend to suffer from acute scarcity due to both environmental and political reasons, including conflict (see, e.g., The Economist, 2017)? I believe that the emphasis on food abundance and its relationship to conflict yields new and important insights into the causes of armed conflict and political violence. This model also has some important policy implications.

Theoretical Contributions

While relatively little research directly addresses the relationship between food insecurity and conflict specifically, numerous studies have implied that such a relationship exists. For instance, in their analysis of the relationship between climate variability and conflict in Sub-Saharan Africa, Burke et al. find that "[t]emperature variables are strongly related to conflict incidence over our historical panel (2009, 20670. See also Miguel, Satyanath and Sergenti, 2004; Koubi et al., 2012). They further hypothesize that, "[t]emperature can affect agricultural yields both through increases in crop evapotranspiration (and hence heightened water stress in the absence of irrigation) and through accelerated crop development...reducing African staple crop yields by 10%–30% per $\circ$C of warming" (ibid. 20672). Somewhat more cautiously, O'Loughlin et al. conclude that "[o]ur study and other studies question the evidence that climatic variability is uniformly driving up the risk of conflict in sub-Saharan Africa," while also noting that "the positive association between instability and temperature may result from the harmful effects of high temperatures on food products such as maize" (2012, 18347).

While these conclusions are supported by subsequent studies (e.g., Raleigh and Kniveton, 2012; Hendrix and Salehyan, 2012; Hsiang and Meng, 2014; Reuveny, 2007), other scholars question the validity of these findings and show that the incidence of conflict is primarily related to political and economic conditions (e.g., Buhaug, 2010). In common to all these studies, however, is the insight that a major mechanism by which climate change can increase the likelihood of conflict is through affecting food supplies.

One important shortcoming of existing research on the relationship between climate and conflict is that extant studies rarely if ever evaluate the role of mediating factors, or analyze how resource scarcity impacts conflict at the local level (Theisen, Gleditsch and Buhaug, 2013). To some extant, this gap has been at least partly filled by a small number of studies that highlight the importance of food scarcity. By and large, the emphasis of these studies is on the manners in which improving food security can mitigate conflict. For example, as was noted above, Hendrix and Brinkman (2013 Brinkman and Hendrix, 2011) claim that in the Sahel, grievances over food motivate some individuals to join rebellions, while food denial can also be used as a tool for counter-insurgency. The potential pacifying effects of food security have also not gone unnoticed by senior policy makers. For instance, the U.S. State Department officially declared in a recent publication that "pursuing a range of specific initiatives in areas such as food security and global health that will be essential to the future security and prosperity of nations and peoples around the globe" (US Department of State, 2010, 33).

While these case-specific studies and policy statements highlight the potential saliency of the relationship between food resources and violence, little has been done in the way of examining this relationship systematically across different contexts, especially at the *highly localized levels*. This deficiency is now being addressed by recent research into the relationship between food import prices and political stability, especially in developing countries. For instance, when studying the relationship between food prices and social unrest globally, Bellemare finds that "rising food prices appear to cause food riots" (2014, 18). Hendrix and Haggard

(2015) expand on Bellemare's study by focusing on the role of political institutions in mitigating the effect of global food prices on instability. They find that, "[g]lobal food prices are correlated with urban unrest in democracies, but not in autocracies" because "food policy in democracies is less biased in favor of urban constituencies" (Hendrix and Haggard, 2015, 145). From a different perspective, Weinberg and Bakker (2015) utilize domestic food prices to operationalize citizen wellbeing. The authors find that social unrest is indeed more prevalent during periods of heightened food prices, with larger price increases being associated with more pronounced increases in social unrest (Weinberg and Bakker, 2015, 320).

These studies highlight an important mediating factor by which variation in food production can affect political instability, but they are also limited in two respects. First, the reliance on food imports may not capture the true effect of food insecurity in countries and regions where locals must, to a large extent, live off locally produced food. Second, the focus on the state as the unit of analysis limits one's ability to account for global and regional variations that might affect food security. In this respect, I echo Theisen, Gleditsch and Buhaug's contention that "more work needs to be put into the geographical disaggregation of the effects of climate change since these effects will not follow national boundaries especially as [a]ctors and agency tend to be vaguely portrayed, or outright ignored, in the relevant empirical literature" (2013, 621-622).

This dissertation complements these existing studies by focusing on one important (mediating) factor, food resources, and the geographic variation of conflict both cross-nationally and at the very local level. Whereas extant research on food prices and imports expands our understanding of the relationship between food, a staple commodity, and political resistance, our understanding of food security's relationship with violent outcomes such as armed conflict is predominately subsumed under the hypothesized effects of trade and/or climate change. However, the implications of food insecurity for conflict are not only a feature of climate change and trade shocks, but also the result of population growth (e.g., Urdal, 2005; Homer-Dixon, 1998), local traditions, global increases in consumption, and droughts, all of which exhibit significant amounts of variation independently of climatic factors.

The focus on geographical variation at the highly disaggregated level thus provides an important complement to existing studies that focus on the nation-state as the main geographic unit of interest, while the emphasis on local food security as an independent variable highlights an important, yet understudied, potential correlate of armed conflict. It is therefore unsurprising that some recent studies have attempted to dedicate more attention these localized effects (e.g., Koren and Bagozzi, 2016, 2017; Wischnath and Buhaug, 2014; Fjelde, 2015; O'Loughlin et al., 2012). These studies, however, suffer from two limitations. From an empirical perspective, these analyses tend to favor static or quasi-static (i.e., made to vary over time by incorporating food prices) measures of cropland as an approximation of local food availability and access. More importantly, these studies (i) do not identify and validate *specific mechanisms* linking food resources to conflict, both locally and globally, and thus rarely, if ever, (ii) connect their findings to *broader theoretical frameworks* on conflict and rebellion.

By theorizing and validating specific mechanisms—namely how the local abundance of food resources generates both possessive and preemptive conflict in high-access areas—and by creating and validating a broad theoretical framework linking local interactions over food to global rebellion patterns, this dissertation thus provides an important contribution to the study of violent conflict. The original high-resolution data used in Chapters 2 and 3 provide an empirical extension to current research, while the theory developed here can be easily applied to current dominant theories that seek to understand the causes of rebellions and civil wars.

The focus on food abundance's role in warfare relates not only to these bodies of research on intrastate conflict, as well as research on the impact of natural resources on civil war discussed in more detail below (e.g., Bannon and Collier, 2003; Collier and Hoeffler, 1998; Le Billon, 2001), but also to studies that are focused on other forms of political violence, such as civilian victimization. Specifically, "instrumentalist" studies of violence against civilians focus on the motivations of state, insurgent, rebel, militia, and terror groups to use violence against civilians, and the factors that influence these groups' tendency to perpetrate atrocities (e.g., Weinstein, 2007; Wood, 2010; Kalyvas, 2006; Hultman, 2007; Fjelde, 2015; Kydd and Walter, 2002). This "instrumentalist" approach emphasizes situations in which violence is used rationally as a means of generating civilian support (e.g., Kalyvas, 2006; Balcells, 2010; Raleigh, 2012), consolidating territorial control (e.g., Valentino, Huth and Balch-Lindsay, 2004), or removing a potential threat (Valentino, 2004). From this perspective, leaders use violence against civilians "when they perceive it to be both necessary and effective" (Valentino, 2004, 67).

Some scholars have applied the logic of strategic violence to non-state actors. Such studies focus on different motivations for violence by non-state actors, including resource extraction (e.g., Salehyan, Siroky and Wood, 2014; Wood, 2010), "contracting" violence (e.g., Raleigh, 2012; Mitchell, Carey and Butler, 2014; Koren, 2017*a*), costly signaling and a display of resolve (e.g., Kydd and Walter, 2002), increasing the costs governments incur from conflict (e.g., Hultman, 2007; Koren, 2017*b*; Wood, 2010), or ethnic motivations (e.g., Fjelde and Hultman, 2014). Similar research also linked violence against civilians natural resources abundance (Azam and Hoeffler, 2002; Esteban, Morelli and Rohner, 2010), and—more recently—to agricultural resources and food security (Koren and Bagozzi, 2017; Bagozzi, Koren and Mukherjee, 2017).

The focus on food resources and the close associations between locally sourced food and atrocities helps can also increase our understanding of the causes of civilian victimization. Many civilian killings during peaceful times might be perpetrated in food abundant regions by groups seeking to strengthen themselves and prepare for future conflicts. Koren and Bagozzi (2017), for instance, find that violence in cropland regions by both state and nonstate groups significantly decreases compared with non-cropland regions during times of relative peace, because armed actors have longer time horizons in respect to interaction with the local population, and thus prefer a strategy of cooptation. However, this tendency reverses itself when conflict intensifies. Time horizons in respect to cooperation shrink, while troops must obtain food for immediate use and the local civilians wish to renege on previous agreements.

Considering that, according to the food abundance and conflict logic, armed conflict and violence against combatants are closely related, I incorporate violence against civilians alongside armed conflict into both the theories developed in the different substantive chapters, and the empirical analyses conducted therein. I do recognize, however, that—in respect to food resources—civilian victimization (during rebellion or otherwise) might arise due to different reasons than those explaining armed conflict between combatant. Therefore, wherever appropriate, I make sure to distinguish between different conflict types, as well as between different actor types. Nevertheless, I do believe—and show—that the focus on food resources and the dynamics of appropriation and preemption can explain a large number of civilian victimization incidents that current research cannot adequately explain.

My food-abundance approach to local and global conflict has several implications to the different bodies of research mentioned above. First, many scholars emphasize the rural nature of civil war, rebellions, and violence against civilians. Kalyvas, for instance, contends that, "most civil conflicts are rural wars, fought primarily in rural areas by predominantly peasant armies" (2004, 2). Yet, as recent studies show (e.g., Bagozzi, Koren and Mukherjee, 2017; Koren and Bagozzi, 2017; Anderson, Johnson and Koyama, 2017), armed conflict—and political violence more broadly—arise not only in rural regions, as many scholars would expect, but also and specifically in agricultural areas. Indeed, to illustrate this latter point, Table 1.1 reports the ratio of 0.5$\circ$ grid cells (as discussed above) that annually experienced (i) civil war with at least 25 combatant deaths observed during the 1990-2008 period (Tollefsen et al., 2012; Gleditsch et al., 2002), and (ii) atrocities with at least five intentional civilian killings occurring within a 24 hour period observed during the 1995-2008 period (PITF, 2009), to different thresholds of a given grid cell's agricultural production, across the *entire globe* (data from Ramankutty et al., 2008).[5]

As Table 1.1 shows, the annual geo-spatial concentration of civil war and atrocities is heavily skewed toward food producing agricultural areas. Cells with any levels of staple cropland constitute only a little more than half of all annual ter-

[5]The two periods, 1990-2008 and 1995-2008, respectively, correspond to years where data for each indicator were available.

restrial grid cells (not counting Antarctica and the Arctic), yet they experienced nearly 90% of all civil wars during the 1990-2008 period, and nearly 100% of all atrocities against civilians with at least five civilian deaths during the 1995-2008 period. This directed relationship persists as the sample is continuously limited to higher and higher thresholds of staple cropland as percent of annual cell coverage. So, for instance, cells in the top 95^{th} percentile of all staple croplands—i.e., where 68.6% or more of the total cell's area is covered with staple cropland—consist only a minute portion of all global annual sample cells (2.8%). Yet, these locations and years experienced nearly one tenth of all civil war events and atrocities against civilians during the temporal periods of concern. Moreover, a very significant portion—38.3%—of atrocities against civilians during the period occurred in areas and years that *did not* experience active conflict. Considering that the lion share of political violence analyses discussed above equates civilian victimization with (civil) war, this observed empirical pattern is puzzling, unless one uses food access to explain it. These linkages thus strongly suggest that both armed conflict *and* violence against civilians are closely linked to food resources and related dynamics.

Another theoretical contribution of a food-abundance approach is in providing an easily-expendable theoretical framework for analyzing the effect of different natural resources on conflict. As mentioned above, previous research linked access to different lucrative resources, such as diamonds and precious ores, to a higher probability of civil war (e.g., Bannon and Collier, 2003; Cilliers, 2000). From this perspective, food can be viewed as lying on a spectrum alongside other important natural resources. Building on research into different "pillars" of food security Barrett (e.g., 2010) or extant FAO frameworks (Food and Agriculture Organization

Table 1.1: The Global Distribution of Civil War, Atrocities, and Cropland

	Ag. Cells Passing Threshold (% Total)	Total Staple Cropland Coverage (%)	Civil War in Ag. Areas, 1990–2008 (%)	Atrocities in Ag. Areas, 1995–2008 (%)
Any staple cropland (out of all terrestrial cells)	735,720 (56.8%)	$c > 0\%$	86.6%	96.6%
25^{th} percentile crop coverage (out of all cropland cells)	551,800 (42.6%)	$c >= 2.6\%$	73.7%	89.8%
50^{th} percentile crop coverage (out of all cropland cells)	367,860 (28.4%)	$c >= 10.5\%$	49.5%	69.8%
75^{th} percentile crop coverage (out of all cropland cells)	183,940 (14.2%)	$c >= 31.3\%$	26.7%	39.2%
95^{th} percentile crop coverage (out of all cropland cells)	36,800 (2.8%)	$c >= 68.6\%$	7.5%	9.1%

Number of observations: $N = 1,296,360$

of the United Nations, 2008), as well as previous research into the relationship between food and war (Koren and Bagozzi, 2016), in Figure 1.3 I conceptualize this spectrum as the hypothetical distance between locations of availability—e.g., fields, mines, wells—and points of access where the final, usable product could be obtained—e.g., ports, lumberyards, markets.[6]

So, for instance, degradable food resources such as vegetables are consumed locally wherever they are grown, without any need for further processing. Similarly, gem stones such as diamonds are found in mines, but then could be placed in one's pocket and carried across the border, where they can be sold in their relatively raw form (although more processing can add value to the final product). Cereals such as maize and potatoes are somewhat different, as they would benefit from some form of processing, although it is not always necessary. Wheat, in contrast, requires processing prior to consumption. This processing can be done at the village level, where a gristmill will turn raw wheat into flour. Timber is similar to wheat in that, again, the raw product must be mobilized to a lumberyard to be processed before being used. Sugar and coffee, in contrast, require regional processing facilities before the final products can be sold on domestic or–more likely—international markets, and even though the agricultural land might be owned by local farmers, processing is usually controlled by the export company (Crost and Felter, 2016). The same is true for precious metals, which necessitate significant levels of infrastructure to be mobilized from the mine to a point where these metals can be processed, and then mobilized gain to a location where the final product can be converted into revenue. Finally, oil is unlikely to be obtained, processed, and sold without establishing control over the entire supply chain, i.e. the state ap-

[6] These framework is valid even if sometimes, as in the case of gems, processing adds value.

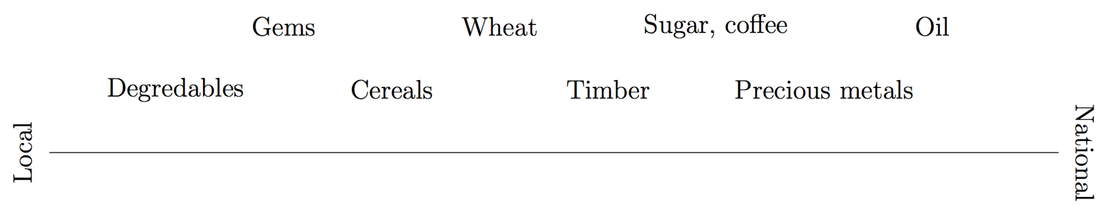


Figure 1.3: The Natural Resources Availability–Access Spectrum

paratus back in the capital and far away from the fields (see, e.g., Englebert and Ron, 2004), although groups such as the Islamic State (IS) highly benefited from oil-related revenues obtained via racketeering and "protection" services (Solomon, Chazan and Jones, 2015).

Linking different natural resources to food and other agricultural resources based on infrastructural traits and parts of the supply chain that need to be controlled can help to identify new directions of research into the "resource course" and its effects (Bannon and Collier, 2003), as well as into the relationship between scarcity, abundance, and conflict more broadly. Moreover, food-based conceptualizations could prove instrumental in cases where measures of local wealth are poorly captured by GDP per capita and related constructs, as is the case for areas where populations earn little income but own large amounts of crop or livestock (e.g., rural Rwanda).[7] In shifting the focus towards alternative ways of conceptualizing wealth and theorizing the role of natural resources, the theoretical framework developed in this dissertation, and especially the emphasis on the impact of abundance, points to new ways in which the political, economic, and geographic approaches to conflict can be synthesized. This can have potential implications not

[7]See, for instance, the concerns raised by the authors of the G-Econ dataset, who emphasize that the quality of their data for developing regions—and especially Africa—is unreliable due to poor resolution and lack of data availability (Nordhaus et al., 2006).

only to research into the causes an consequences of conflict and political violence, but also policymakers working to ameliorate conflict and prevent conflict renewal locally.

Policy Contributions

Brandt, Freeman and Schrodt correctly argue that, "[s]cholars and policymakers want to anticipate intra- and international conflicts. They also want to evaluate what might have occurred if certain actions had been taken in the past and (or) what might happen if governments take certain actions in a given conflict in the future" (2011, 41). Through archival research and detailed statistical analysis, this dissertation presents the opportunity to develop new quantitative tools for researchers and policymakers concerned with conflict prevention and the broad implications of food insecurity. The mixed-methods approach used here is designed to aid policymakers in determining the level of impact various food insecurity issues have on conflict and rebel violence across the developing world. This information can directly assist in protecting vulnerable populations and inform policymakers and others working for peace about triaging and addressing critical issues related to food insecurity. Moreover, as shown in Chapter 3, information on the local dynamics of food and conflict can also be leveraged to *forecast* future violence at the highly-localized level.

Many researchers and policymakers will likely find the notion that food resources impact conflict unsurprising, perhaps even somewhat trite. Yet, a more nuanced understanding of the micro-dynamics at work in specific regions will allow for a more meaningful policy application to take place. The measures used to approximate food abundance can also be used to identify in advance whether conflict might occur in a given region during a given period, and whether any region or country, conflict-afflicted or not, will experience high levels of civilian victimization. Highlighting the salience of food insecurity indicators in our ability to understand and predicting different forms of violence thus directly relates to the emphasis placed by many non-governmental organizations such as the United States Institute of Peace (USIP) on "groundbreaking work and training on conflict analysis, electoral violence prevention, early warning systems, and preventing genocide and mass atrocities."

The focus on food abundance can also serve to enhance work intended to counter violent extremism by informing common practices of conflict management related to violence between two non-state armed groups. Scholars and policymakers tend to focus on conflict between states or between a state and a rebel group, but have paid relatively little attention to conflicts in which both groups are not affiliated with the state, such as rival ethnic militias. Yet, examples of recent conflicts from Sierra Leone (Keen, 2005) and the Horn of Africa (Mkutu, 2001; Sundberg, Eck and Kreutz, 2012), among others, show that armed non-state groups do fight each other often.

Moreover, this model can also illuminate some less-understood aspects of the peace-building processes in regions that are in danger of experiencing violence or conflict renewal. By highlighting the more violent aspects of competition over food resources, the abundance model suggest that complementing traditional peace-building practices with improvements to food resource access (e.g. resources management of grazing land by the state, building water reservoirs and dams) can help conflict-prone regions overcome food insecurity, reducing the need to compete over food resources by violent means. Indeed, the potentially pacifying effects of food security have also not gone unnoticed by senior policy makers. In addition to the statement by the U.S. State Department mentioned above, the Food and Agriculture Organization of the United Nations stresses the importance of food system resilience and warns that, "[i]ncreasing incidence of drought may force people to migrate from one area to another, giving rise to conflict over access to resources in the receiving area. Resource scarcity can also trigger conflict and could be driven by global environmental change" (2008). The theories and empirical models developed in this dissertation can thus help to inform policy-related work to focus not only on the linear relationship between scarcity and conflict—so prevalent in policymaking circles—but also on the complex realties of food resources-based conflict, which might exhibit the opposite trends to these expected by policymakers.

The Plan of the Dissertation

Drawing on the theoretical framework laid out in this introductory chapter, the ensuing chapters develop and test different interrelated theories, and identify specific mechanisms linking food abundance with conflict, both locally and globally. Considering the potential role of scarcity-based, socioeconomic, and macro-political explanations as crucial confounders, these chapters also account—both theoretically and empirically—for a variety of different mechanisms implied by these alternative approaches. Hence, many of the empirical analyses are focused on (sub-Saharan) Africa, the world region most frequently analyzed by scarcity centric studies. Nevertheless, when evaluating the impact of food resources at the macrolevel in Chapter 4, I rely on a *global* sample so as to illustrate the validity of a food resources-based conflict framework to an international scale, and across all world regions.

Chapter 2 is a comprehensive study of the impact of local variations in staple crop yields on conflict in Africa. I apply the framework of food abundance to identify and evaluate the validity of the most fundamental mechanism hypothesized by this argument, a mechanism I term, as mentioned above, “possessive conflict” over food security. I first develop a theory to explain why and when food resource abundance generates conflict, as different groups seek to obtain food resources for personal consumption, the most fundamental mechanism hypothesized in the theoretical discussion presented in this chapter. I provide historical background showing that such conflict is rather prevalent in the developing world; and discuss how the need to obtain food resources shapes local conflict trends, focusing on four different actor types with different motivations to initiate possessive conflict over food resources. I then evaluate this theoretical framework empirically on highly-localized, *time varying* data on conflict and staple crop yields in Africa, which provides a novel contribution to the research on civil war. Because food production cannot be claimed to be exogenous to conflict, I use negative rainfall shocks, droughts, to identify the direct relationship of food production on conflict, while illustrating—both empirically and theoretically—this instrument’s robustness to violations of the exclusion restriction.

Empirically, this chapter provides quantitative evidence linking past internal armed conflict incidence to food yields at the very local level while incorporating variations in climatic trends, specifically droughts. Using 0.5 decimal degree grid cells (10,674 cells for Africa) (Tollefsen et al., 2012), the influence of annual local wheat and maize yields (Ray et al., 2012) on violence is estimated using ordinary least squares (OLS) and two-stage least squares (2SLS) regressions with grid-cell (i.e., unit of analysis) fixed effects. Unlike previous analyses, which employ only climate-related variables, focus on specific countries, or employ only binary indicators of conflict (Burke et al., 2009; Maystadt and Ecker, 2014; Koren and Bagozzi, 2016; O'Loughlin et al., 2012), this chapter relies on subnational analysis of the *annual* effect of local food crop production in Africa on continuous measures of conflict within all 0.5 $\circ$ grid cell for the years 1998-2008.

In Chapter 3 I consider a different mechanism linking conflict to food resource abundance. As mentioned above, I term this mechanism "preemptive conflict" over food security, because it involves actors using violence primarily to cut their rivals off from accessing necessary food resources, either by seizing control over these resources or by destroying them. Using a game-theoretic commitment problem model backed by statistical analysis and systematically collected anecdotal evidence, I show that the aim of preemptive conflict is to increase one's overall chances of victory against the armed forces of other communities, governments, or rebels by draining their sources of food support. This model revolves around the strategic calculi of (i) the first group, or defense forces, (ii) the second group, or raiders, and (iii) the civilian producers that provide local food support to the defense forces. When the local civilians increase their level of food support, they correspondingly increase the probability that the defense forces will win in combat. Moreover, this level of support cannot be known to the raiders in advance. In equilibrium, the raiders anticipate that if more food support is available to the defense forces, their own chances of victory will diminish.

The implication is that above a certain probability threshold of the defense forces' victory, the possibility of high food support levels becomes a grave threat. I find that in the model, this incentivizes the raiders to *preemptively* target regions with more food resources in order to cut the defense forces off from these sources of support, and increase their (the raiders') overall probability of victory. I use this model to derive a statistical-strategic model to empirically test this mechanism by modeling the behavior of armed groups and civilians as a game with sequential moves. I use similar data to those used in Chapter 2 to test this model, although with different conceptualizations of the dependent and independent variables. In illustrating that this strategic model also improves the *predictive* strength of forecasting models of localized conflict compared with a non-strategic model, I also show that this model has substantive value.

Similarly to Chapters 2 and 3, Chapter 4 begins with a microlevel evaluation of the historical role of food in one important context: the Mau Mau rebellion in 1950s Kenya. This case has the advantage of (i) containing detailed information on the conduct of a food denial campaign by the colonial forces, specifically (which is not easy to come by), and (ii) the fact that few studies have made use of these sources, which means that many of the documents, especially those related to food denial, are revealed here for the first time. Both factors thus allow me not only to provide a detailed discussion of the role played by nutritious, durable resources during the rebellion, but also to set these interactions in a *historical context.* Therefore, to generate microlevel evidence and validate pertinent mechanisms operating locally, I analyzed archival resources from the British National Archives as part of a mixed-methods approach to this research. Combined with historical literature, these archival resources—some of which became available only recently—allow me to construct a comprehensive case study and explore the historical role food resources play in rebellion.

Documents from deliberations of British officials during the campaign illustrate that these officials were acutely aware of how important food resources—and especially nutritious, calorie-rich staple crops—were to the Mau Mau fighting efforts. Importantly, these officials understood that these resources were critical not only because they allowed the group to adequately feed its members, as hunting and foraging could provide similar sustenance levels, but also because regular access to staple crops enabled the Mau Mau to support its members more *efficiently*, which contributed to the group's cohesion and improved its troops' morale. Using an original geo-spatial dataset I constructed from additional archival documents, geographic patterns of violence during the Mau Mau rebellion are also tested *quantitatively* to evaluate these claims.

To complement these microlevel findings, the second part of Chapter 4 includes an examination of whether the localized patterns identified in the microlevel models are relevant to explaining the (i) probability and (ii) duration of rebellions worldwide over the same period. These two expectations are tested using a maize-based indicator of food production, while accounting for a large number of alternative explanations. Maize was chosen to approximate food production because, as a highly nutritious staple, it was identified in archival sources as having substantial impact on the behavior of Mau Mau rebels, although I also show that this effect persists across other cereals. Robustness models are used to additionally account, to the extent possible, for the potential endogeneity between food and rebellion using relevant instrumental variables. These different models confirm both hypotheses derived from my microlevel analysis: nutritious staple crops significantly and substantively increase the likelihood and duration of rebellions. This chapter's findings thus validate the theoretical argument developed above, and shows that conflict scholars should account for food resources in their theories and analyses.

Chapter 2: Food Abundance and Possessive Conflict over Food Security

In Chapter 1, I laid out and explained the economic rationale behind the broad argument that, contrary to previous expectations (e.g., Burke et al., 2009; Maystadt and Ecker, 2014; Miguel, Satyanath and Sergenti, 2004; Homer-Dixon, 1998), conflict is driven by higher food productivity, on average, and not by scarcity. In this chapter, I identify and evaluate the validity of the most fundamental mechanism hypothesized by this argument, a mechanism I term *possessive conflict*. I first develop a theoretical framework to explain why and when food abundance generates conflict in order to allow different groups to secure food for personal consumption. I then evaluate this theoretical framework empirically on highly-localized data on conflict and staple crop yields in Africa, which are used to approximate local food resource availability in a manner similar to that used in past research (O'Loughlin et al., 2012; Koren and Bagozzi, 2016, 2017).

One challenge in empirically evaluating the role of staple crop yields in driving conflict is that local food production variables are inherently endogenous; food output can influence the propensity of violence, but the associated feedback effects from conflict can in turn influence food output (Homer-Dixon, 1998; Messer, 2009).

To address this concern, the local staple crop yield indicators used here are instrumented using drought intensity levels, which—as recent studies have posited—can influence conflict through food production. The causal relationship between local food production and violent conflict is thus identified using this climatic variable (Miguel, Satyanath and Sergenti, 2004; Bellemare, 2015). It is important to stress that previous research has suggested that rainfall variations mightnot be an ideal instrumental variable of income shocks (Sarsons, 2015). While the argument developed here does not necessarily equate local yields with income, I address this concern in two main ways. Theoretically, I discuss some distinctions of African agriculture systems, the empirical focus on analysis. Empirically, I show that my drought-based instrumental variable is at least "plausibly exogenous" (Conley, Hansen and Rossi, 2012).

This chapter provides quantitative evidence linking past internal armed conflict incidence to food yields at the very local level while incorporating variations in climatic trends, specifically droughts. Using 0.5 $\circ$ grid cells (10,674 cells for Africa) (Tollefsen et al., 2012), the influence of annual local wheat and maize yields (Ray et al., 2012) on violence is estimated using ordinary least squares (OLS) and two-stage least squares (2SLS) regressions with grid-cell (i.e., unit of analysis) fixed effects.[1] Conflict measures were obtained from the Armed Conflict Location and Event Dataset (ACLED) Version 6, which provides exceptional disaggregated coverage of political violence in Africa at the very local level (Raleigh et al., 2010). Unlike previous studies, which employ only climate-related variables, focus on specific countries, or employ only binary indicators of conflict (Burke et al., 2009;

[1] I show that my decision to rely on this model is reasonably robust by re-estimating a series of Generalized Method of Moments (GMM) regressions to obtain more efficient estimates for dynamic panel data (Blundell and Bond, 1998; Arellano and Bond, 1991).

Maystadt and Ecker, 2014; Koren and Bagozzi, 2016; O'Loughlin et al., 2012), this study relies on sub-national analysis of the *annual* effect of local food crop production in Africa on continuous measures of conflict within all 0.5 $\circ$ grid cell for the years 1998-2008.[2]

The focus on Africa as the world region currently most susceptible to the effects of food insecurity—through climatic variability or otherwise—corresponds to previous studies on climatic variation, food security, and conflict, which similarly focus on the same region (Burke et al., 2009; Buhaug, 2010; O'Loughlin et al., 2012). Moreover, the availability of *localized* data on political violence is also the best for Africa, as the world region most susceptible to conflict. Indeed, the Armed Conflict and Location and Event Data (ACLED) Version 6 dataset (Raleigh et al., 2010) used here covers a wide variety of violence types at the highly localized, village level (as discussed in more detail below). Importantly, although this analysis is focused on Africa, its lessons are applicable to other global contexts, as shown in Chapter 4.

The findings presented here contribute significantly to our understanding of the relationship between food security, violent conflict, inequality, and environmental variability. The estimation procedure accommodates both the non-random assignment of observations and the possible concurrent relationship between climate, food production, and conflict. Overall, the empirical models provide new and nuanced evidence that locally grown food resources have a particularly strong influence on the frequency of conflict in Africa. In the IV models, where the effect of food resources is exogenized with respect to conflict, *higher* levels of food crop

[2]The temporal period for which information on all variables was available. See also Adhvaryu et al. (2016) for a study that relies on similar resolution levels for analyzing conflict across sub-Saharan Africa.

yields are shown to have a substantive effect on violent conflict, all else equal.

These findings challenge the notion that rising food scarcities increase conflict simply by forcing communities and armed groups to compete over a shrinking pool of food resources. Rather, empirical evidence suggests that—on average—violent conflict is not the direct result of food scarcity, but of abundance; areas with more food resources are more valued by different actors, and as a result attract more conflict. Moreover, these associations are robust to a variety of alternative explanatory mechanisms and specifications. The relationships between climatic variability, food, and violence are therefore complex and warrant careful interpretation. Indeed, as shown in the next chapter, other mechanisms exists that can also explain violence over food resources, and which are distinct for the simple necessity to secure resources solely for possession.

Food Security and Possessive Conflict Over Time

In many parts of the world, conflict over possessing food resources is not a recent phenomenon, engendered by climate change, but rather a persistent historical occurrence.

Background

The association of food and violence has always been part of the human narrative. Throughout history, armies and militias living off the land were a regular characteristic of warfare. In ancient and medieval times, before the development of modern logistic support technologies, living off the land, foraging, and relying on the local population was a military necessity (e.g., Kress, 2002, 10-15). Although the utilization of logistic supply chains has significantly reduced the need of modern militaries to rely on local populations for support, the bureaucratic and economic capabilities required to maintain such systems has ensured that the vast majority of armed groups in Africa lack regularized support (Koren and Bagozzi, 2016).

Deficiencies in access to food have forced many contemporary armed actors to routinely live off the land in times of war and peace. During the Civil War in Sierra Leone, for instance, regular Sierra Leone Army (SLA) troops were paid not with money, but with bags of rice, a meager payment usually appropriated by generals located back in the capital, Freetown. This lack of support pushed the SLA to fight over areas with higher levels of food resources and to perpetrate atrocities against local populations in order to extract sustenance (Keen, 2005). The appropriation of food and the abuse of power by military officials was not unique to Sierra Leone, and very similar situation existed in other African countries such as Angola (Cilliers, 2000, 8-9). In some instances, leaders actively encouraged troops to commandeer such supplies from the population. In Zaire, for instance, Mobutu Sese Seko notoriously replied to his troops when the latter complained about not being paid their wages: "you have guns; you don't need a salary" (Stearns, 2011, 115).

The importance of securing food resources in face of unequal access is not the unique domain of groups that are part of the government vs. rebel logic. Indeed, ethnic and tribal militias and other irregular forces representing local communities and different ethnic groups might be even more likely to initiate conflict over food resources. As discussed below, these communities might be especially dependent on locally grown food resources, and hence more susceptible to the adverse effect of distributional differentials between the core and the periphery (Reardon and

Taylor, 1996; Pitt, Rosenzweig and Hassan, 1990). This situation is especially likely in countries and regions where little or no protection of property rights by the government exists, which leads to the formation of these irregular militias (Koren and Bagozzi, 2017).

In the extant literature, conflict between rebel and irregular groups over food resources is usually attributed to competition over livestock, especially cattle. For instance, Rockmore (2012) finds that in Uganda, populations residing in areas of persistent conflict shift from large cattle herds and open grazing to small livestock that can be kept in closed compounds, as well as labor intensive and drought intensive crops.[3] Similar patterns appear in Colombia, where households reduce land allocated to perennial crops and increase production of seasonal crops and pasture in regions with an intense conflict (Arias, Londoño and Zambrano, 2014).

Indeed, scholars that study cattle theft in Africa argue that "[t]he practice is causing great havoc in the area in terms of loss of human lives, destruction of property, stealing of livestock and dislocation of populations" (Osamba, 2000). For instance, in South Sudan, where "[e]thnic groups have fought each other over cattle—a vital part of the indigenous economy—for centuries" (Reuters, 2011), cattle theft and reprisals are responsible for a large portion of combatant and noncombatant casualties. These dynamics are by no means unique to South Sudan. As a result of similar dynamics, in the Horn of Africa states applied significant force to combat violent raiders, who attempt to steal food resources or secure access to fertile regions (Leff, 2009; Maystadt and Ecker, 2014). Even in relatively stable countries such as Ghana, competition between farmers and Fulani herders frequently leads to localized conflict (Tonah, 2006).

[3]See also Finnström (2003) for an anthropological perspective.

By attributing livestock and violence dynamics to competition over access to water resources, some studies have drawn links between environmental change, conflict, and food resource abundance (e.g., Butler and Gates, 2012; Adano et al., 2012).[4] For instance, in their analysis of conflict in Kenya and Ethiopia, Adano et al. find that "more conflicts and killings take place in wet season times of relative abundance, and less in dry season times of relative scarcity, when people reconcile their differences and cooperate" (2012, 77). Somewhat in line with this argument, Rowhani et al. find "that conflicts are more frequent in regions with more vegetation," presumably because vegetation increases the ease with which raiders can approach cattle pens unnoticed (2011, 221).

These studies and their emphasis on abundance are thus in line with research into the positive impact of profitable natural resources on civil war and civilian victimization (e.g., Bannon and Collier, 2003). In other words, just like areas and countries with abundance of profitable resources such as diamonds or oil attract violence, so should be the case in areas with higher food available—these areas offer more of an especially valuable resource, which not only can be traded for profit, but is also necessary to guarantee survival. Regional narratives, especially analyses of Uganda (Rockmore, 2012) and Colombia (Arias, Londoño and Zambrano, 2014), highlight violence resulting not only from cattle raids, but also from food crop resources. Some additional examples include Angola (Cilliers, 2000), Sudan and Ethiopia (Leff, 2009), Somalia (Ahmed and Green, 1999), Sierra Leone (Keen, 2005), and Nigeria (Ofuoku, 2009), and Mozambique (Hultman, 2009). Forces initiating conflict in regions where food resources are abundant or moving into

[4]Other studies, however, identify a negative relationship. For instance, Maystadt and Ecker (2014) associate droughts with more civil war in Somalia.

these areas in order to control these resources is therefore a modern-day affliction in many African, and other developing, countries and regions (Koren and Bagozzi, 2016).

Food Security Vulnerabilities

Constraints on food access are unlikely to lead to acute violence within advanced industrialized democracies due to the existence of safeguards to those in need and a high degree of infrastructure that can transfer more food when needed. However, in many developing African countries and regions, widespread limitations to food access can affect armed conflict. This is because such food insecurity-prone areas are likely to be characterized by three main attributes.[5] First, rural regions in many African countries have poor infrastructure, including an absence of paved roads and refrigeration, which have especially parlous implications in relation to food security (Food and Agriculture Organization of the United Nations, 2008). Individuals in these regions are therefore at a higher risk of having their immediate access to food impaired.

A second attribute of regions with a high risk of food insecurity is a relative lack of sophisticated agricultural technology, such as heavy machinery and efficient fertilizers (Barrett, 2010; Kastner et al., 2012). This technological gap is narrowing, but current technology is still limited, and the impact of inadequate farming technology is much more severe in underdeveloped regions (Barrett, 2010; Lybbert et al., 2007; Kastner et al., 2012). Without technological improvements, less food can be produced in these regions, and thus they are more prone to food shortages.

[5] The term "food insecurity" refers to situations where food security levels are dangerously low, and there are not enough food resources, due to either distributional or production shortages, to guarantee sufficient dietary intake for all individuals in the region (Barrett, 2010).

Lastly, rural regions in the developing world, and especially in Africa, are arguably most vulnerable to the negative impact of climatic variability on food accessibility (Food and Agriculture Organization of the United Nations, 2008; Reardon and Taylor, 1996). The weak infrastructure that characterizes many of these regions (e.g. dirt roads) is much more likely to be destroyed due to extreme climatic effects such as flood. For instance, a report by the Food and Agricultural Organization of the United Nations states that, "climate variables also have an impact on physical/human capital—such as roads, storage and marketing infrastructure, houses, productive assets, electricity grids, and human health—which indirectly changes the economic and socio-political factors that govern food access" (2008, 12).

Taking into account these three issues, people in many developing regions are forced to rely on food produced and sold locally and grown using relatively simple technology, which increases asymmetries in access to food, both between urban and rural areas (Pitt, Rosenzweig and Hassan, 1990), and—within rural areas—between commercial producers and smallholders (Jayne et al., 2003). Moreover, although numerous studies highlight the potentially salient effect of food imports on production (Bellemare, 2015; Hendrix and Haggard, 2015), food imports are less relevant to the daily diet of many individuals in these regions compared with foodstuff that are locally grown and sold (see, e.g, Barrett, 2010; Koren and Bagozzi, 2017). This places these individuals at a high risk of experiencing food insecurity (Barrett, 2010; Rowhani et al., 2011), especially from a distributional perspective (Reardon and Taylor, 1996; Pitt, Rosenzweig and Hassan, 1990).

This historical evidence illustrates that the linkage between conflict and food resources is not a recent phenomenon, engendered by climate change, but rather—in many parts of the world—a persistent historical occurrence. Yet, when discussing possessive conflict over food resources, and conflict over food resources more broadly, it is important to distinguish between four different categories, each with different motivations to initiate food-related conflicts, or to move into areas with more food during times of ongoing war. The first category includes official military and auxiliary state forces that do not receive (regular) support from the state, a fact which distinguishes them from other, better organized state forces. This category includes most official state forces in Africa (Henk and Rupiya, 2001), as well as political militias. Indeed, numerous militia groups such as the *janjaweed* in Sudan or the *interahamwe* in Rwanda were especially likely to be sent to pray upon the local population, sometimes with logistic support being withdrawn from them intentionally to push them toward violent appropriations of food resources (Koren and Bagozzi, 2017). Unsupported state actors are thus likely not only to initiate conflict in areas with abundant food resource, but also gravitate toward these areas in search of necessary food support during times of war.

The second category of actors includes all rebel groups and similar nonstate actors operating against the government. These groups might attack areas with more food in order to possess these resources not only to support themselves or challenge state strongholds, but also to exploit local food resources for profit (Crost and Felter, 2016), which sometimes results with high levels of civilian victimization (Koren and Bagozzi, 2017). For instance, in Uganda, rebels are likely to appropriate and kill profitable cattle, leading to a shift in local populations' agricultural portfolios (Rockmore, 2012). Similarly, the Islamic State in Syria and Iraq (ISIS) fought to establish and maintain control over fertile agricultural areas due to the group's reliance on agricultural income (Jaafar and Woertz, 2016).

The third category covers militias and civil defense forces representing *agriculturalist* communities in rural regions. The agriculturalist lifestyle is more characteristic of areas where access to water resources is relatively stable, allowing these communities to grow crops for consumption and to be sold locally (O'Loughlin et al., 2012). Individuals and groups in these localities thus live a stationary lifestyle, and procure livestock mostly as a means of wealth accumulation (i.e., as an equivalent of a savings account) (Rockmore, 2012; Roncoli, Ingram and Kirshen, 2001). In many countries these communities are less likely to be defended by the state due to the costs involved with sending and supporting armed groups. This in turn means that property rights are rarely enforced (Barrett, 2010), pushing many of these communities to resort to self-help. Such self-defense militias can be used not only to defend against potential raids, but also to attack neighboring communities in order to establish control over more arable land and food resources. Indeed, this last point is supported by ample anecdotal evidence, as was shown above.

The fourth category includes all militias representing *pastoralist* communities. Pastoralists are highly mobile groups that live in mostly arid regions. As a result, these groups are forced to rely on mobile livestock, especially cattle, rather than on crops, meaning that in this case owning cattle is not a luxury but rather a necessity dictated by their (semi-)nomadic lifestyle (Lybbert et al., 2007). Pastoralists have been at the heart of many previous studies connecting food resources to conflict, with some associating increases in precipitation with higher frequencies of raids (e.g., Adano et al., 2012; Butler and Gates, 2012), while others showing the opposite relationship (O'Loughlin et al., 2012; Maystadt and Ecker, 2014). In many cases, regional narratives emphasize how the prevalence of violent conflict is shaped by local conditions such as the precedence of civil war, which floods the region with firearms (Koren and Bagozzi, 2017), or the collapse of state authority, especially if external actors move into the vacuum and fund raids (Rockmore, 2012). Pastoralist militias might therefore both raid other pastroalists in order to replenish their herds, and attack agriculturalist communities in order to both steal livestock and obtain food crops, which—due to their mobile lifestyle and the arid regions where they reside—pastoralist communities are generally incapable of growing independently.

All four actor categories, which—it is important to acknowledge—might exhibit significant overlap, have different motivations to fight over food resources. In the first two cases, given that troops are frequently mobile rather than stationary, they do not have the ability to grow food for personal consumption, and as a result must rely on food grown locally in the region in which they operate (Koren and Bagozzi, 2016). Agricultural land can be owned by local civilians who grow food for personal consumption only or by larger producers who grow food for trade, both internationally and domestically. Especially in regions without developed infrastructure and where mobilizing food resources or appropriating food aid is less possible, both government and rebel troops are forced to move into areas that offer access to food in order to support their operations. These limitations intensify the incentives for troops to seek out the few remaining areas that do have high food access for sustenance, and potentially also for rent-extraction (Jaafar and Woertz, 2016; Crost and Felter, 2016).

In the latter two cases, while agriculturalist and pastoral communities can produce food for personal consumption, they are also under a constant threat of experiencing acute food insecurity (as discussed in the "Food Security Vulnerabilities" subsection above). The eruption of a disease or the onset of drought can suddenly kill crops and decimate herds, placing these communities at the sudden and immediate risk of starvation. Without government support or other safety nets that can mitigate the effects of these unexpected shortages, acute food insecurity is a Damocles Sword over the heads of these groups (Barrett, 2010). For example, during the drought in Burkina Faso, "farmers strove to minimize cash investments in agriculture, but in some cases they were unable to do so because many had consumed all their seed before planting" (Roncoli, Ingram and Kirshen, 2001, 128). Such shocks jeopardize *immediate* food security; assuming the community survives this adverse period, it should be able to restore food supply levels. This suggests that cooperation might emerge as a preferred strategy in these contexts (Adano et al., 2012; Toft, 2006; Butler and Gates, 2012). However, to increase overall resilience, improve capabilities, and be better prepared to the brutal effect of shocks, such groups will be expected to increase competition during periods of abundance.

Without the ability to purchase drought-resistant seeds or livestock, and without government or international support—which in many cases cannot arrive in time or be received by those who need it— that provides safety net against sudden shocks, the only alternative to free market or aid solutions is to obtain food using violent means. Moreover, the tendency for conflict might also be affected by population growth (Homer-Dixon, 1998) or migration (Dell, Jones and Olken, 2014), which increase the pressure to secure more resources just to keep the same level of sustenance, leading to a zero-sum, "Red Queen" scenario.[6] To increase overall resilience, communities must obtain the necessary access to enough food resources during periods of plenty, when more assets could be mustered and when time horizons in respect to the competition over food are relatively long, i.e., actors *perceive* that more resources will make them more resilient in the future. This directly relates to the notion of time horizons in interstate war, as put by Toft: "if both actors discount the present but see their fate provided for in the future, then violence is likely" while "[i]f both actors discount the future highly, then violence is unlikely" (2006, 56).

Finally, it is important to emphasize that while conflict frequency might increase with higher yields, food is not always necessarily the cause. For instance, government or rebel troops might be stationed in more fertile areas in order to protect these areas or to support themselves. Consequently, other armed actors seeking to attack enemy strongholds will move into these areas not to obtain food resources, but simply because these regions are likely to offer a valuable target. In these contexts, the impact of food resources is indirect; a military base might have been formed in this particular region to protect local food resources or simply because support is more likely there, and fighting arose as enemy forces attacked this base. Moreover, while food resources might be a direct cause of armed conflict in some cases, conflict—especially full-scale civil war—is frequently the result of political and socioeconomic issues (Fearon and Laitin, 2003). In these situations, troops gravitate into areas with more food resources during ongoing war to secure

[6]Building on Lewis Carroll's apt description, a "Red-Queen" race is a competitive scenario, in which every actor must match or exceed the current expenditures of rivals, so that each is forced by the others to invest even more resources only to maintain the same position (Baumol, 2004, 238).

food or prevent these resources from being consumed by the enemy (Koren and Bagozzi, 2016). Therefore, while I make the argument that conflict concentrates in areas with high staple crop yields, I also recognize that groups do not fight *necessarily* over these resources; locations with more food resources might simply attract and sustain a large portion of ongoing violence.

Whether competition over food resources is the direct cause of conflict, or whether it directly or indirectly fuels ongoing violence, in contrast to some previous studies of the climate-conflict nexus (Burke et al., 2009; O'Loughlin et al., 2012; Maystadt and Ecker, 2014) the expectation here is that conflict should be positively associated with *more* food resources, all else equal. However, although multiple studies have suggested that such positive associations exist (e.g., Koren and Bagozzi, 2016; Adano et al., 2012; Butler and Gates, 2012), making a causal statement with respect to food resources is more challenging because, unlike temperature or precipitation, at the local level, food crops are likely to have an endogenous relationship with conflict. In other words, just as higher local food outputs can cause conflict, conflict can destroy crops and reduce yields.

For instance, as Messer argues, "[f]ood poverty may be exacerbated as violence disrupts migratory labor and remittance patterns over wide regions, as has been the case across multiple African areas, also Afghanistan and Iraq, whose violence, and interruptions to livelihood and security, impact neighboring countries" (2009, 15). Violent conflict can destroy infrastructure, displace large populations, and increase population pressures via movement of different groups and troops into the region (Koren and Bagozzi, 2017). Moreover, food insecurity can be used as a weapon of conflict in-and-of itself, as adversaries deliberately starve opponents into submission by siege or destruction of crops, livestock, and markets, and divert food relief from intended beneficiaries to armed groups and their supporters. Indeed, research into the impact of conflict on food choices found significant changes in livestock and crop growing patters in Uganda (Rockmore, 2012) and Colombia (Arias, Londoño and Zambrano, 2014). Establishing the *causal* effect of food on conflict—or come as close to it as possible when observational data are concerned—necessitates an identification strategy and effective data that allow the researcher to isolate the causal arrow flowing from food resources to conflict rather than the other way around. Such a strategy would allow me to evaluate the hypothesis that, at the highly localized level, conflict should (on average) be more frequent in years of abundance.

Data and Methods

This section discusses the data to be analyzed, the equations to be estimated and the identification strategy to be used to establish the causal impact of food resources on armed conflict.

Data

For Africa, a grid cell sample encompassing 11 years of data from 1998 to 2008 is used to evaluate the relationship between local food crop yields and violent conflict. The geolocated data used for this analysis were obtained from the PRIO-Grid dataset (Tollefsen et al., 2012). The PRIO-Grid dataset measures a variety of spatial data at the 0.5 $\circ$ resolution, or a geographic squared "cell" of roughly 55 $\times$ 55 kilometers at the equator (3025 square kilometers area), which decreases with higher latitudes. This dataset thereby allows one to capture the variation of specific geographic and economic phenomena globally (excluding oceans, Antarctica, and the Arctic) at the very local level. All variables were aggregated to the same grid level and integrated into this dataset for the years analyzed.

The dependent and continuous *conflict* variable was obtained from the ACLED Version 6 dataset and measures all incidents of political violence (including those that ended without casualties), with a focus on civil and communal conflicts, violence against civilians, remote violence, rioting and protesting that occurred both within and outside the civil war context (Raleigh et al., 2010). The actors covered by this dataset are official state forces, rebels, political militias, ethnic and tribal militias, protesters, and rioters, which means that more than any other available dataset, the ACLED Version 6 data corresponds directly to the different actor categories discussed in the previous section. The ACLED dataset covers incidents at the village/town level, which were aggregated to the annual 0.5 $\circ$ grid level. The ACLED dataset also provides information on geographic specificity, i.e., whether an incident was coded at the village/town, district, or province level. To ensure comparability across different cases and variables, I analyze only events coded as occurring at the village/town level, which most closely correspond to my grid-cell level of analysis.

The resulting *conflict* indicator is therefore defined inclusively as the total number of political violence incidents among and between different state and non-state actors within a given cell during a given year coded by the ACLED dataset. This indicator captures many nuances of political violence—including events that ended without casualties, such as strategic developments—and hence provides an improvement over other studies that employ binary indicators of conflict or focus exclusively on the state vs. rebel logic. Additionally, and again in line with the argument presented above, these data capture both instances of conflict onset and violence occurring as part of ongoing campaigns. For summary purposes, averaged values by grid cell of *conflict* are plotted for the 1998-2008 period in Figure 2.1 below.

The effect of local food availability on the number of conflict events is evaluated using the annual local productivity of wheat and maize—two cereals that together compose the lion's share of all staple crops consumed in African households (Food and Agricultural Organization of the United Nations, 2016). These continuous *wheat yield* and *maize yield* indicators measure average annual levels of wheat and maize productivity at the highly localized, $\sim 0.08\circ$ grid level, or approximately 9km x 9km at the equator (Ray et al., 2012).[7]

To identify local areas where cropland is grown, Ray et al. (2012) relied on an earlier high resolution geospatial global cropland map for year 2000 created by Ramankutty et al. (2008). Ramankutty et al. (2008) utilized two sources of data to create their map. The first source were global satellite-based land cover data obtained from two previous datasets, BU-MODIS and GLC2000 (Ramankutty et al., 2008, 7-8). The second source were national and subnational census data on cropland area and food inventories. The authors then used regression techniques to train the satellite land cover data against the census data. The resulting estimates along with the satellite data allowed Ramankutty et al. (2008) to then map cropland areas at the high-resolution 5 minute ($\sim 0.08\circ$) level. In the second step, Ramankutty et al. (2008, 11-12) further adjust their high-resolution maps, scaling up or down all pixels within an administrative unit to exactly match the census data.

[7]For detailed information on the sources and methods used to compile these data, see, Monfreda, Ramankutty and Foley (2008, 4-9), Ramankutty et al. (2008, 6-10), and Ray et al. (2012, Supplementary Information, 11-15).

To interpolate their time-varying measure of crop-specific area and yield by 0.08 $\circ$ grids for wheat and maize, Ray et al. (2012) then expanded the dataset developed by Ramankutty et al. (2008) in two steps. First, Ray et al. (2012, Supplementary Information, 6-12) collected an exceptionally large number of datasets crop area and yields at the subnational and national level, going back to 1961. The average number of census observations over the 1961-2008 period was 600,000 per crop, although the number of observations varied geographically.[8]

Ray et al. (2012) then use the high-resolution cropland map created by Ramankutty et al. (2008) as a spatial reference to disaggregate wheat and maize area and yield data within each administrative unit. The grid of staple crop yields was created "by disaggregating the yield from the smallest political unit with available data in the agricultural inventory by distributing the inventory data for each administrative unit uniformly to each pixel [i.e., 0.08 $\circ$ grid] within that administrative unit" (Monfreda, Ramankutty and Foley, 2008, 10). For wheat and maize yields, the process developed by Monfreda, Ramankutty and Foley (2008) was repeated annually over the 1961-2008 period (Ray et al., 2012, Supplementary Information, 11-12). The crop area in each 0.08 $\circ$ grid of the final map was set to zero when no reference to a crop existed in the inventory data. Information on these missing points was then interpolated from the latest five years if at higher administrative units crops reports were present (Ray et al., 2012, Supplementary Information, 12).[9]

It is important to note that data quality might be poor in some countries,

[8]Crop inventory information became more easily available after 1990, the period analyzed here (Ray et al., 2012, Supplementary Information, 11).

[9]While Ray et al. (2012) also calculate changes in staple crop yield trends using categorical trend indicators, the present article relies on the raw high-resolution yield information underlying the analyses conducted in Ray et al. (2012).

sometimes due to ongoing political strife, which means that some countries do not provide annual reports. These issues, however, are unlikely to affect the specific data used here. First, the geospatial and temporal interpolation of missing data as discussed above should help ameliorate some missing-ness issues resulting from ongoing strife. Moreover, the authors created a useful metric (presented in Ray et al., 2012, Supplementary Information, 12) to evaluate overall data quality for each political unit. As shown in Ray et al. (2012, Supplementary Information, 1), the data quality for Africa is generally high at the reported administrative level (averaging within the top 90th percentile) and—with a data quality level that is nearly identical to North America's—is better than any other world region. It is important to emphasize, however, that the vast majority of crop output data on Africa were available only at the national level. Thus, for most African countries Ray et al. (2012) interpolate localized changes in wheat and maize yields within each particular 0.08 $\circ$ grid based on national averages, which is less than ideal.

These limitations notwithstanding, the resulting *wheat yield* and *maize yield* indicators provide "a dramatically improved understanding of crop yield and area changes across regional and global scales, which are otherwise often obscured using only national census statistics" (Ray et al., 2012, 2), especially in world regions where subnational statistics are missing or nonexistent, such as Africa. Indeed, as highlighted by 24 food-system experts, a salient problem with current attempts to assess local food security is that, "the data collected are rarely comparable across ecological zones because of inconsistencies in methodologies or in the spatial scale at which observations are made" (**?**, 558). From this perspective, the high-resolution data produced by Ray et al. (2012) provide a significantly and substantively better fit for observed local food production trends, even when compared with other high-resolution datasets such as BU-MODIS or GLC2000. Using a dataset that combines satellite-derived imagery and staple crop inventory data also allows scholars "to capitalize on whichever satellite-based land cover data set is best suited to each region," compared with the constituent datasets, which on their own would provide "reasonably good global results, but would lose accuracy in some regions" (Ramankutty et al., 2008, 10).

To ensure comparability to the other data used in this present study, both the *wheat yield* and *maize yield* indicators were averaged to the 0.5 $\circ$ grid cell level to ensure comparability across observations. A value of one thus corresponds to a grid-cell whose total area is entirely covered by wheat or maize crops, respectively, during a given year. For summary purposes, averaged values for *wheat yield* and *maize yield* (by grid cell) are plotted for the 1998-2008 period in Figure 2.4 below, and summary statistics of wheat yields, maize yields, and conflict for each African country in the sample are reported in Table 2.1. These figures all strongly suggests that, as hypothesized above, higher conflict frequency correlates with food abundance, not scarcity.

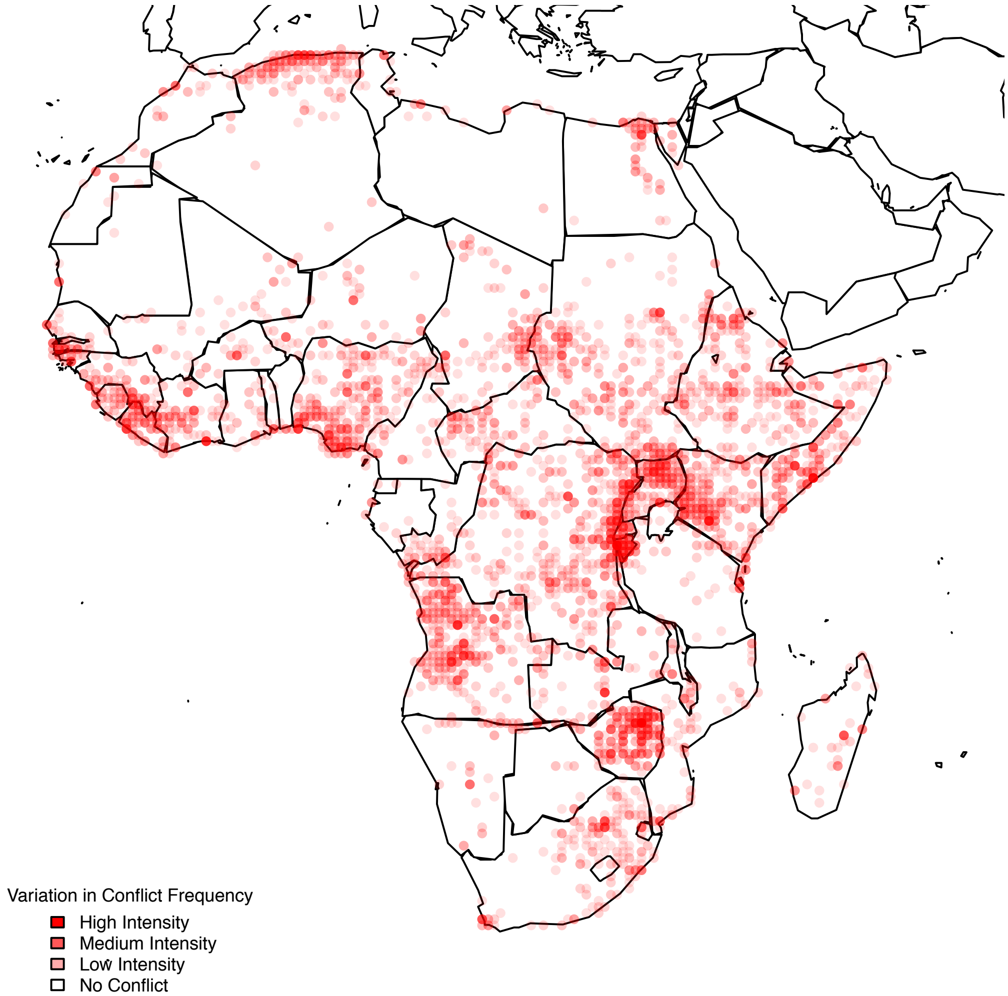


Figure 2.1: Average levels of violent conflict from ACLED Version 6 dataset by 0.5 ∘ grids (Raleigh et al., 2010).

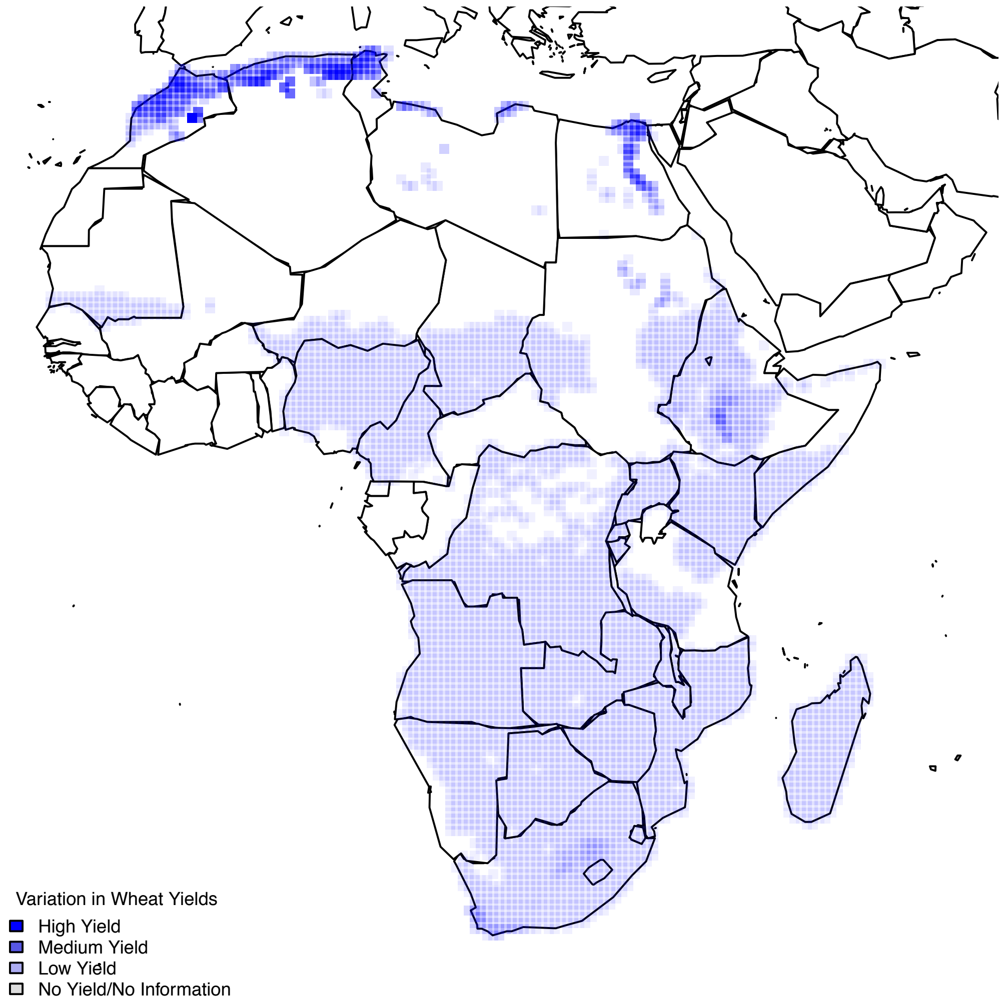


Figure 2.2: Average wheat yields by 0.5 ∘ grids (Ray et al., 2012).

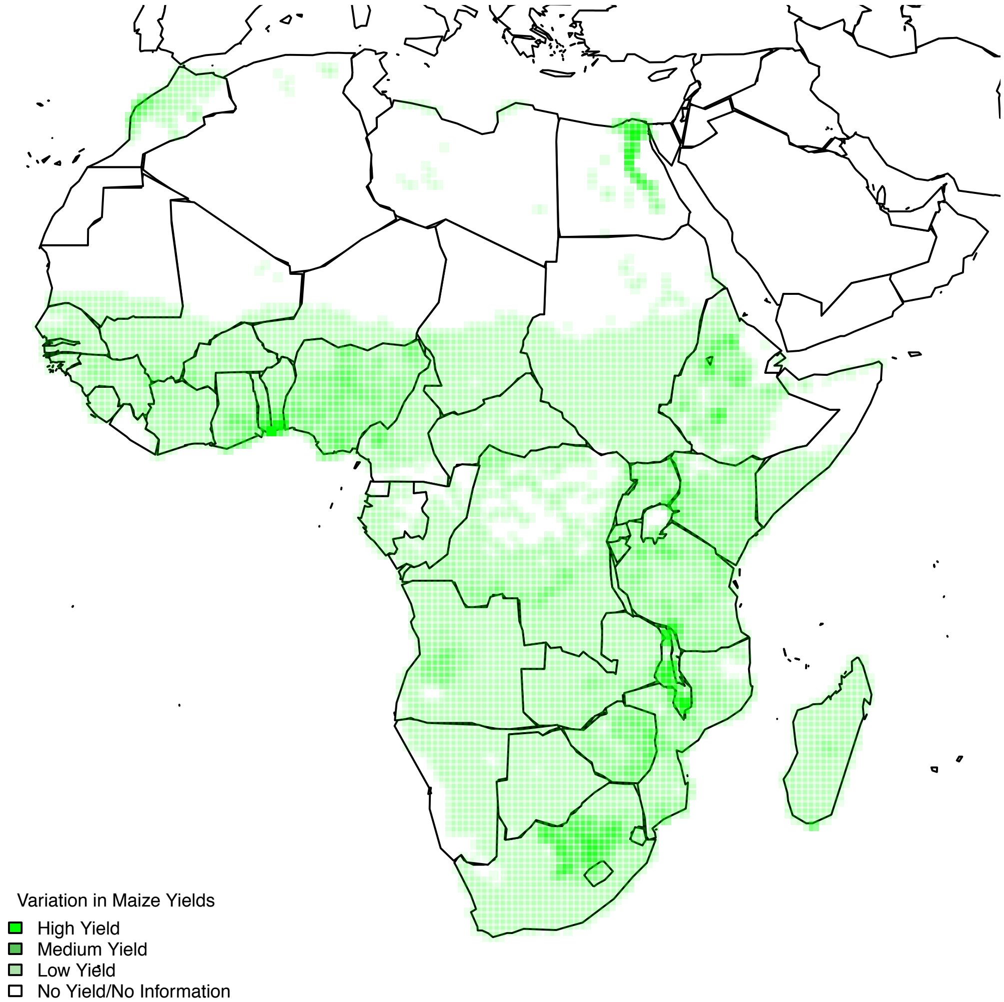


Figure 2.3: Average maize yields by 0.5 ∘ grids (Ray et al., 2012).

The instrument used to identify the direct effect of the effect of food on conflict (or, in other words, to "exogenize" it), *drought*, is operationalized using a Standardized Precipitation Index (SPI) that aggregates monthly precipitation data to the cell-year level (Guttman, 1999). This SPI-based indicator classifies drought severity as the number of standard deviations below average precipitation levels in a particular grid cell during a given year. The resulting *drought* variable is an ordinal indicator (it can take the values of 0, 1, 1.5, and 2.5 standard deviations

Table 2.1: Summaries of conflict events, average wheat, and average maize yields by grid cell, total values for all countries analyzed, 1998-2008

Country	**Conflict events**	**Average wheat yield**	**Average maize yield**	**Country**	**Conflict events**	**Average wheat yield**	**Average maize yield**
Cabo verde	0	0	0	Burundi	2,463	0.0423	0.4780
Sao Tome	0	0	0	Rwanda	230	0.0380	0.3720
Guinea-Bissau	147	0	0.0817	Somalia	3,397	0.0135	1.0068
Eq. Guinea	14	0	0.0241	Djibouti	24	0	0.0002
Gambia	56	0	0.0506	Ethiopia	794	3.0997	4.5400
Mali	82	0.0353	1.1529	Eritrea	343	0.1095	0.0841
Senegal	305	7.11E-05	0.4805	Angola	2,594	0.0106	3.2023
Benin	21	0.0001	2.5372	Mozambique	155	0.0103	5.9677
Mauritania	57	0.0019	0.0478	Zambia	420	0.0505	2.3872
Niger	190	0.0189	0.1412	Zimbabwe	3,599	0.1884	5.6793
Cote d'Ivoire	846	0	1.2375	Malawi	98	0.0258	6.4863
Guinea	356	0	1.0685	South Africa	757	3.8579	12.9092
Burkina Faso	103	1.91E-05	1.2364	Namibia	156	0.0076	0.1231
Liberia	775	0	0.0259	Lesotho	6	0.1118	0.6114
Sierra Leone	3,416	0	0.1278	Botswana	25	0.0075	0.2449
Ghana	66	0	2.8605	Swaziland	60	0.0008	0.1913
Togo	61	0	1.7980	Madagascar	210	0.0200	1.3267
Cameroon	107	0.0016	2.0153	Comoros	0	0	0
Nigeria	1,978	0.1621	12.6989	Mauritius	0	0	0
Gabon	23	1.65E-06	0.2436	Seychelles	0	0	0
Cen. Af. Rep.	319	0.0002	0.5243	Morocco	188	18.0346	1.6961
Chad	406	0.0080	0.6261	Algeria	1,348	16.8551	0.0116
Rep. Congo	196	9.21E-05	0.1506	Tunisia	47	5.3266	0
Dem. Rep. Con.	3,023	0.0304	7.3598	Libya	61	2.5095	0.0188
Uganda	3,255	0.0474	2.7439	Sudan	2,256	1.6689	0.3036
Kenya	2,095	0.4928	5.8295	Egypt	367	7.9396	5.7286
Tanzania	245	0.2256	8.4878				

Note: A value of "1" corresponds to a quantity that is equal to one 0.5×0.5 degree grid cell that is entirely (i.e., 100%) covered by maize or wheat producing cropland, respectively.

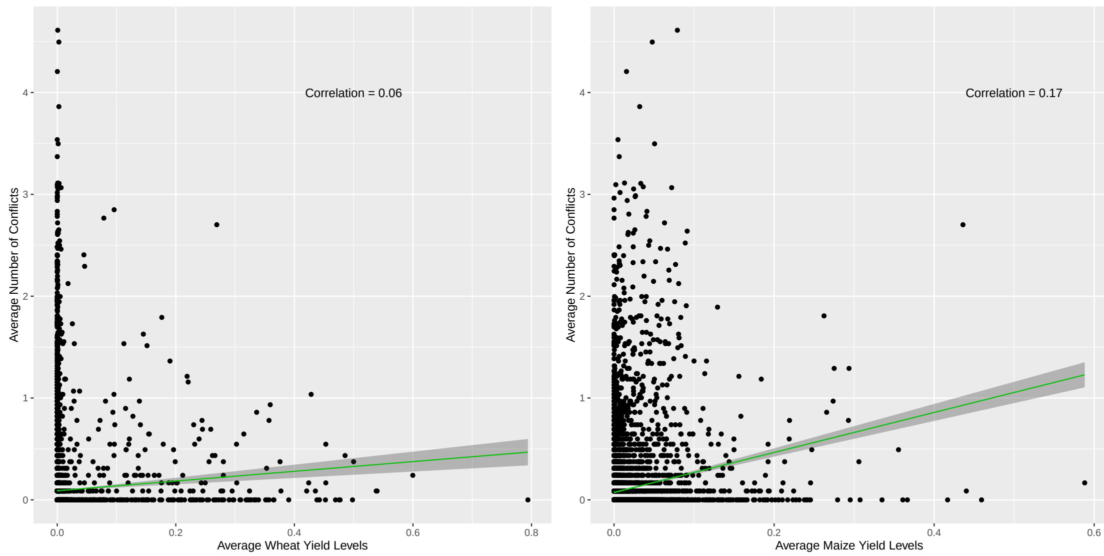


Figure 2.4: The linear correlation between annual wheat (left) and maize yields (right) and conflict by 0.5 ∘ grids, 1998-2008. Conflict measures are presented in natural log form.

below the mean) providing a straightforward measure of rainfall shocks and—correspondingly—their impact on food production. This variable and its validity is discussed in great detail in the next section.

The main models reported below also employ different controls for important potential confounders. First, considering the potential impact of population pressures on food availability and the number of conflict events as raised by previous studies (e.g., Homer-Dixon, 1998), I account for population density in a given cell during a given year using the variable *population* (Nordhaus, 2006). This cell-level variable was originally measured for the years 1995, 2000, and 2005 and then interpolated to the yearly level using a last-value-carried-forward approach (Tollefsen et al., 2012). To control for spatial correlation, I include a binary spatial lag of the dependent variable, *conflict (spatial)*, denoting whether any conflict events occurred in the first-order neighboring cells. I also include a one-year lag of the dependent variable, *conflict (lag)*, to control for the temporal dependence of conflict events, alongside annual and grid cell fixed effects.

Crucially, these variables are all measured at the grid cell, and not country, level. Furthermore, the crop yield measures used for analysis are *time varying*, which provides a major improvement over past studies of this sort that have favored static measures of cropland at comparable levels of geographic resolution (e.g., Koren and Bagozzi, 2016; O'Loughlin et al., 2012). Nevertheless, to account for alternative explanations (e.g., Fearon and Laitin, 2003; Bannon and Collier, 2003), several country level indicators were also included in analysis. The *democracy* measure is the ordinal Polity2 indicator, with higher values corresponding to more democratic regimes (Marshall, Jaggers and Gurr, 2013). The gross domestic product (GDP) per capita measure, *GDP per capita*, was obtained from the World Bank (2012). Finally, a large number of alternative mechanisms are evaluated in the Competing Mechanisms section below. For summary purposes, all variables—including those used in sensitivity analyses —are reported in Table 2.2.

Identification Strategy

Local food yields cannot be argued to be exogenous to localized conflict, because the latter might devastate infrastructure in the region and generate more population pressures (e.g., via troops moving in). This suggests that the estimates provided by OLS regressions are likely to be biased due to simultaneity between the main explanatory variable and the dependent variable. The identification strategy

Table 2.2: Summary Statistics of All Variables

	Minimum	Median	Mean	Max	SD
Grid Cell Level Variables					
Conflict	0	0	0.228	334	2.854
Wheat yield	0	2.63e-05	0.009	0.930	0.047
Maize yield	0	0.004	0.016	0.667	0.034
Drought	0	0	0.229	2.5	0.654
Conflict (lag)	0	0	0.182	334	2.523
Conflict (spatial)	0	0	0.091	1	0.287
Population[1]	0	9.721	9.369	16.268	2.263
Nighttime light	0.021	0.034	0.040	0.941	0.032
Ethnic diversity	0	1	1.325	7	1.177
Terr. change	0	0	0.007	1	0.081
Temperature	3.625	24.675	24.382	32.617	3.774
Temperature (lag)	3.625	24.658	24.364	32.617	3.778
Wheat yield (lag)	0	2.58e-05	0.009	0.930	0.047
Maize yield (lag)	0	0.004	0.016	0.642	0.034
Violent conflict	0	0	0.069	220	1.209
Violent conflict (lag)	0	0	0.055	220	1.038
Military conflict	0	0	0.103	286	1.726
Military conflict (lag)	0	0	0.081	286	1.550
Conflict[1]	0	0	0.062	5.814	0.320
Conflict (lag)[1]	0	0	0.047	5.814	0.289
Any drought	0	0	0.123	1	0.328
Severe drought	0	0	0.088	1	0.283
Extreme drought	0	0	0.062	1	0.241
Country Level Variables					
Democracy	-9	0	0.214	10	5.084
GDP per capita[1]	5.517	7.350	7.547	10.341	1.106
Food imports (%)	0.474	16.493	17.313	62.416	7.510
Agricultural imports (%)	0.146	1.175	1.870	42.322	3.040
Foreign aid[1]	15.713	20.040	19.947	23.240	1.269
Oil production[1]	0	13.592	9.170	18.690	8.075
Gas production[1]	0	0	1.663	7.192	2.369
Military expenditure[1,2]	0	12.612	12.536	15.350	1.645
Cereal prod. index	0.015	91.957	99.050	882.89	57.648
Meat prod. index	0.032	91.620	93.835	737.38	52.157

[1] natural log

[2] This variable is only available for the years 1998-2007

used in this article therefore relies on the use of an instrumental variable (IV), i.e., a variable that is correlated with food production but arguably uncorrelated with the error term of violent conflict. This framework is in line with previous studies of the relationship between agriculture and economic growth, climate, and conflict (e.g., Miguel, Satyanath and Sergenti, 2004; Sarsons, 2015; Bellemare, 2015).

Recall that an IV must satisfy two requirements. First, it must be correlated with food production at the local level. To this extent, Table 2.4 shows that the instrument is not weak, excluding, perhaps, the Full specifications. Second, the IV must only affect violent conflict through food production, a requirement that is also known as meeting the exclusion restriction (Angrist and Pischke, 2009).

To account for the potentially endogenous relationship and "feedback effects" between violent conflict and food production, and obtain consistent estimates, I rely on the ordinal *drought* indicator discussed above, which is crucially measured at the annual grid level, in a manner consistent with previous research (e.g., Miguel, Satyanath and Sergenti, 2004; Crost and Felter, 2016). As a climatic indicator, this instrument is highly unlikely to be directly endogenous with violent conflict. At the same time, this instrument is likely to be highly correlated with local wheat and maize yields, which means that the IV models identify the true relationship between food security and conflict, conditional on droughts, and are thus preferred to their OLS counterparts. This is easily ascertained with statistical tests—in effect, tests of the null hypothesis that the instrument is weak—the results of which are shown in Table 2.4. Moreover, the effect of droughts on food production and on increasing food scarcities has been the tenet of previous studies of the climate-conflict nexus (e.g., O'Loughlin et al., 2012).

The use of the IV *drought* combined with unit-of-analysis fixed effects also helped to tackle concerns related to unobserved heterogeneity, measurement error, and reverse causality. First, in addition to the two requirements from a valid IV—that it is exogenous to the dependent variable and that it is correlated with the endogenous explanatory variables, both of which have been discussed and analyzed both qualitatively and quantitatively in the main paper—one can add a third requirement; that the IV will have a monotonic effect on the dependent variable (Angrist and Pischke, 2009; Sovey and Green, 2011). The term "monotonic effect" refers to the notion that the instrument does not impact the instrumented endogenous variable differently in different locations, and not produces a positive impact in some and a negative impact in other locations. If this requirement is satisfied, then the average LATE of food yields is weighted in respect to conflict throughout the entire sample.

This requirement highlights one advantage of using droughts as the instrument; as mentioned above, drought ought to decrease yields everywhere in Africa, and not causes decreases in some grid cells, but increases in others. The effect of drought on conflict through maize and wheat yields is thus monotonic, because in every grid cells and years where drought effected conflict through food production, it did so in the same way, with higher levels of drought translating to lower food crop yields, while the absence of drought causes higher yields. Moreover, while the use of rainfall shocks as an IV to approximate shocks to growth has been questioned by some due to its predictability (as discussed in detail below), the annual variation in droughts—strong, negative shocks—is less predictable, and the use of annual fixed effects controls for increases in droughts that are time dependent. Last, recall that although it is plausible that conflict can affect food crop yields, a reverse causality between conflict and drought is quite implausible; rather, the causal arrow most likely flows from droughts to conflict.

It is important to recognize, however, that previous research suggested that—in some situations—rainfall shocks might not necessarily pass the exclusion restriction. Sarsons (2015), for instance, relies on information on dam construction in India to illustrate that while income in downstream areas is less sensitive to rainfall fluctuations, rainfall shocks remain a strong predictor of riots in these contexts. As this is not a trivial concern, I address it both theoretically and empirically. First, note that, perhaps even more so than in India (the focus of Sarson's study), most agriculture in Africa (especially Sub-Saharan Africa) during the ten-year period analyzed here depended almost exclusively on rainfall (Food and Agriculture Organization of the United Nations, 2008; Kastner et al., 2012). As a result of this high dependence on precipitation, the amount of land required to produce food in these regions actually increased over time, as opposed to Asia, where researchers observed notable decreases in the amount of land required to support a certain number of people (Kastner et al., 2012).

These context-specific differences suggest that, at least from a theoretical perspective, the use of *drought* as an instrument for the impact of local food yields on conflict in Africa is defensible. Moreover, rainfall can impact conflict through both positive and negative deviations from the mean, with too much precipitation causing overly high levels of soil moisture, thus increasing the risk of crop disease (Food and Agriculture Organization of the United Nations, 2008). This suggests that the impact of being located down- vs. upstream from irrigation dams as identified by Sarsons (2015) is more likely during positive rainfall shocks. To help accounting for this concern, I restrict my *drought* instrument to focus only on *negative* rainfall shocks as discussed above. This approach also builds on Dell, Jones and Olken, who note that, "[a] promising direction for research on droughts would construct a drought definition based solely on exogenous environmental variables such as precipitation" (2014, 755).

I also address this concern empirically. First, note that Sarsons shows that the violation of the exclusion restriction for rainfall-based instruments is the results of location, specifically, rather than issues such as conflict spillovers or migration (2015, 67-68). This in contrast to the latter's impact of economy-wide effects at the country level, where these and other channels might be at play (Carleton and Hsiang, 2016; Dell, Jones and Olken, 2014). To account for constant factors such as geographic locations at the highly disaggregated geo-spatial level, I include fixed effects for each grid-cell in my sample and cluster standard errors at a similar level to address heterogeneities. Considering the relatively small size of this unit of analysis (0.5 x 0.5 grid) compared with, say, the province or even district levels, this approach should help fix much of the geo-spatial variance within my sample, including variance resulting from upstream vs. downstream locations.

More importantly, however, I rely on the method developed by Conley, Hansen and Rossi (2012) to allow for departures from the exclusion restriction, i.e., allowing the IV to have some direct effect on conflict that is not exclusively restricted to food yields, to show that this IV is still "plausibly exogenous." Briefly, Conley, Hansen and Rossi (2012) identify that, often, the exclusion restriction is suspect because many IVs are endogenous to some extent. To test how much a given IV violates the exclusion restriction, they accordingly present several practical methods for performing inference while relaxing the exclusion restriction and showing that an IV can pass a certain threshold of endogeneity but still remain exogenous enough for the purpose of inference. Indeed, as shown in Table 2.6 and discussed in more detail below, the IV *drought* survives local-to-zero approximation tests for "plausible exogeneity," suggesting that—empirically—the use of this IV is defensible (Conley, Hansen and Rossi, 2012).

If the instrument is valid and effectively exogenizes food production relative to conflict, then the coefficients for *wheat yield* and *maize yield* are the weighted average, covariate specific local average treatment effects ("average LATE") of food production on violent conflict, i.e., the increase in the extent of violent conflict (as measured by the continuous dependent variable) due to food production in those grid cells and years where droughts induce a change in maize and wheat yields, accounting for other covariates (Angrist and Pischke, 2009, 130). Hence, the relationship between food production and conflict at the local level is identified using the following two-equation system in the IV models:

$$y_{it} = \alpha_1 + \beta_{1f}\hat{f}_{it} + \beta_{1y}y_{i,t-1} + \beta_{1s}y_{st} + \beta_{1X}X_{it} + \mathbf{\Phi_{1i}} + \mathbf{\Psi_{1t}} + \epsilon_{1it} \tag{2.1}$$

$$f_{it} = \alpha_2 + \beta_{2c}c_{it} + \beta_{2y}y_{i,t-1} + \beta_{2s}y_{st} + \beta_{2X}X_{it} + \mathbf{\Phi_{2i}} + \mathbf{\Psi_{2t}} + \nu_{2it} \tag{2.2}$$

Where y_{it} is a vector of violent conflict incidents by grid cell for each year; $y_{i,t-1}$ is the temporal lag of the dependent variable; y_{st} denotes whether conflict occurred in neighboring cells or not each year; X_{it} is a matrix of control variables; $\mathbf{\Phi_i}$ are $\mathbf{\Psi_t}$ are fixed effects by grid cell and year, respectively; α are the constants for each equation;[10] ϵ_{1it} is the error term for the second stage regression and ν_{2it} is

[10] These intercepts are not included in the regression outputs below as all variables are demeaned and the "within transformation" is applied to multiple factors (Gaure, 2013).

the error term of the first stage regression. In this system, $\hat{f}_{it}$ is the instrumented effect of wheat or maize yields as estimated by equation 2, i.e., the increase in the extent of violent conflict (as measured by the dependent variable) due to wheat or maize yields in grid cells and years where drought, captured by the vector c_{it}, induces a change in crop yields. Due to the panel nature of the data, heterogeneity of errors across years is a possibility, and hence grid cell-clustered standard errors for all models are used to assess statistical significance.

To treat the observed quantities on all variables for each cell as non-random, fixed effects for each grid cell were included in all models; and fixed effects for each year covered in the data (1998-2008) were also included to account for potential time dependencies. The use of unit of analysis fixed effects—i.e., including binary variables for the units of analysis, in this case grid cells, to capture observed and unobserved influences on an outcome of interest (the frequency of conflict in this case) that are constant over time—is a well-established statistical procedure for identifying causal relationships (Angrist and Pischke, 2009). This approach, combined with the use of a valid instrument to "exogenize" the effects of the endogenous explanatory indicators, allows the IV models to isolate localized food production effects and make the case for a consistently significant higher risk of conflict with increased yields.

Results

To evaluate the effect of local food yields on conflict I estimate two separate specifications for each crop. These models build on the availability and access aspects of food security as described by Barrett, two concepts that are "inherently hierarchical, with availability necessary but not sufficient to ensure access" (2010, 825). Considering that food availability is "typically measured in daily calories per person" (Barrett, 2010, 825), the Baseline—or availability—model includes only food yields, i.e. the total amount of wheat or maize available in a given grid cell during a given year (exogenized by *drought* in the IV models) in addition to grid cell and year fixed effects to account for constant observed and unobserved confounders. Building on the definition of food access as "the range of food choices open to the person(s), given their income, prevailing prices, and formal or informal safety net arrangements through which they can access food" (Barrett, 2010, 825), the Full specifications incorporate a variety of controls (discussed in the previous section) alongside food yields to account for the impact of salient political and socioeconomic conditions.

Table 2.3 reports the coefficient estimates of four OLS models that each assesses the likelihood of cell-year conflict in Africa. The effect of these variables is then compared to their average LATE in Table 2.4. The first-stage regression estimates for the IV models are reported and discussed in Table 2.5 below. The hypothesized relationship between food productivity and conflict is evaluated against benchmark explanations of conflict risk: socioeconomic and political indicators, and conflict history (Fearon and Laitin, 2003; Bannon and Collier, 2003). The linear effect of wheat and maize yields on conflict without accounting for endogeneity concerns is estimated in Models 1-4. The exogenized effect of these indicators on localized conflict is then estimated in a series of IV regressions in Models 1E-4E.

In Model 1, *wheat yield* has a negative but statistically insignificant effect on conflict. However, by destroying infrastructure, causing civilian producers to flee,

Table 2.3: OLS regression models for total number of conflict events per grid cell, 1998-2008

	Wheat Yield		Maize Yield	
	1) Baseline	**2) Full**	**3) Baseline**	**4) Full**
Wheat yield	-0.517	-0.528	–	–
	(0.464)	(0.472)		
Maize yield	–	–	-3.749**	-3.111***
			(1.682)	(1.188)
Conflict (lag)	–	0.202**	–	0.202**
		(0.084)		(0.084)
Conflict (spatial)	–	0.337***	–	0.336***
		(0.083)		(0.083)
Population[1]	–	-0.663***	–	-0.633***
		(0.190)		(0.187)
Democracy	–	-0.022**	–	-0.022**
		(0.010)		(0.010)
GDP per capita[1]	–	0.019	–	0.024
		(0.173)		(0.172)
Observations	72,213	68,204	72,213	68,204
R^2	0.454	0.429	0.454	0.429
Adjusted R^2	0.400	0.370	0.400	0.370

* indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$ (two-tail test).
Cell values are OLS regression coefficient estimates with standard errors clustered by grid-cell in parentheses. Grid cell and year fixed effects included in each regression though not reported here.

[1] Natural log

or through "scorched earth" tactics, conflict might also negatively impact food production. This coefficient estimate might thus reflect, at least partly, the effect of conflict on food yields, which obscures the true effect of local yields on violence. Model 1E, where the effect of local food production with respect to conflict is instrumented using *drought*, accounts for this likely scenario. Here, *wheat yield* is positively and significantly associated with the incidence of conflict, which suggests that conditional on average conflict in a given cell, localized conflicts arise more often during years of *high* yields.

The Full (or "access") specification presented in Models 2 and 2E include a variety of controls to show that these results are indeed consistent with the addition of a large number of socioeconomic, political, and spatial-temporal confounders. Here, the effects of GDP per capita, democratization levels, population density, as

Table 2.4: IV regression models for total number of conflict events per grid cell, 1998-2008

	Wheat Yield		Maize Yield	
	1E) Baseline	**2E) Full**	**3E) Baseline**	**4E) Full**
Wheat yield	75.13***	83.53***	–	–
	(24.35)	(26.05)		
Maize yield	–	–	184.40***	204.74***
			(58.90)	(62.77)
Conflict (lag)	–	0.201**	–	0.206**
		(0.084)		(0.084)
Conflict (spatial)	–	0.343***	–	0.436***
		(0.087)		(0.110)
Population[1]	–	-0.877***	–	-2.762***
		(0.239)		(0.798)
Democracy	–	-0.032***	–	0.007
		(0.011)		(0.013)
GDP per capita[1]	–	-0.048	–	-0.336
		(0.180)		(0.246)
Observations	72,169	68,160	72,169	68,160
Endogenous variables test	9.520***	10.28***	9.809***	10.64***
Weak instrument F-statistic (clustered SEs)	50.22	8.372	51.48	8.955
Weak instrument F-statistic (i.i.d. SEs)	191.39	31.84	88.74	15.26
R^2	0.414	0.351	0.366	0.264
Adjusted R^2	0.354	0.284	0.301	0.187

* indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$ (two-tail test).
Cell values are IV regression coefficient estimates with standard errors clustered by grid-cell in parentheses. Grid cell and year fixed effects included in each regression though not reported here. The variables *wheat yield* and *maize yield* were instrumented using *drought*.

[1] Natural log

well as spatial and temporal conflict dependencies are evaluated, in addition to the *wheat yield* variable included in Models 1 and 1E. While the effect of within-grid cell wheat production on violent conflict in Model 2 is again statistically insignificant, the instrumented effect of *wheat yield* is positive and statistically significant in Model 2E, even with the inclusion of these alternative explanations. This again confirms the argument that, on average, years with *higher* yields increase the frequency of conflict within a given cell.

Models 3-4 and 3E-4E estimate the same specifications, this time using maize as an approximation of local food availability. The effect of maize yields is negative and significant in the Baseline and Full models for the OLS regressions. Yet, in the IV models *maize yield* is consistently *positive* and significant across both the Baseline and Full specifications. These findings again support the hypothesis that conflict within a given grid cell is likely—on average—to arise during years with higher yields, when the conditional impact of droughts on annual yields by grid cell is estimated. Moreover, diagnostic regressions of the instrument *drought* on the yield variables presented in Table 2.5 below, are significant, suggesting that the IV estimates are indeed informative (Angrist and Pischke, 2009).[11]

The estimated impact of staple crop yields on local conflict frequency is sizable: focusing on Model 1E as the benchmark, the average marginal effect for *wheat yield* indicates that a 0% to 100% change in wheat yields increases the predicted number of conflict events in a given grid cell during a given year by approximately 75 incidents. This suggests that for a mere 1% increase in *wheat yield*, the predicted number of conflict events by cell increases by approximately 0.75 incidents. Con-

[11] For all specifications, statistically significant (to the five percent level) Hausman test estimates suggest the random effects assumption is less likely to be supported by the data, thus supporting the use of a fixed effects framework.

sidering that the average number of conflict events for an average grid cell, during a given year for the entire 1998-2008 period, is 0.228, this effect is substantial.

More broadly, endogenous variable tests are significant, suggesting that endogeneity between the dependent and explanatory variables likely exists and thus supporting the use of IV models. In Models 1E and 3E the F-statistic for a weak instrument far exceeds the threshold of 10 (Stock and Yogo, 2002) for an IV not to be considered weak, while in Models 2E and 4E the instrument is borderline weak when clustered standard errors are used, suggesting that this model might be marginally biased toward OLS estimates. Thus, this analytical framework and the consistency of the results across different specifications suggest that positive local food yields have a strong impact on localized conflict in Africa. This effect is not unique to one crop, but rather characterizes at least two distinct staple foods. Crucially, Models 2E and 4E clearly show that this finding is not the result of local population densities, higher levels of state presence, or economic development, all of which are controlled for by these models.

Before proceeding to the sensitivity analysis, the first stage regression estimates of the 2SLS models from Table 2.4 are provided in Table 2.5. As can be clearly observed, *drought* has a highly statistical effect (to the 1 percent level) on both *wheat yield* and *maize yield*. Moreover, the R^2 values of all models are exceptionally high, with the (adjusted) R^2 of the Baseline models being higher than that of the Full models, suggesting that *drought* is an especially good fit for instrumenting food yields in Africa. Additionally, the fact that the instrument *drought*'s effects on both food yield indicators is significant to the 1% level is important, because instruments with no observable correlation with the endogenous explanatory variable cannot be considered truly valid (Angrist and Pischke, 2009, 87-89).

Table 2.5: IV regression models for total number of violent events per grid cell, 1998-2008 – first stage estimates

	Wheat Yield		**Maize Yield**	
	1E) Baseline	**2E) Full**	**3E) Baseline**	**4E) Full**
Drought	-8.539e-04***	-8.966e-04***	-3.478e-04***	-3.658e-04***
	(1.205e-04)	(1.265e-04)	(4.848e-05)	(4.990e-05)
Conflict (lag)	–	6.456e-06	–	-1.998e-05*
		(1.197e-05)		(1.204e-05)
Conflict (spatial)	–	-1.043e-04	–	-4.947e-04***
		(2.444e-04)		(1.448e-04)
Population[1]	–	2.153e-03***	–	1.009e-02***
		(5.726e-04)		(1.067e-03)
Democracy	–	1.230e-04***	–	-1.418e-04***
		(1.099e-05)		(1.779e-05)
GDP per capita[1]	–	9.749e-04***	–	1.807e-03***
		(1.489e-04)		(4.081e-04)
Observations	72,169	68,160	72,169	68,160
R^2	0.959	0.958	0.972	0.972
Adjusted R^2	0.954	0.954	0.970	0.969

* indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$ (two-tail test).
Cell values are IV regression coefficient estimates with standard errors clustered by grid-cell in parentheses. Grid cell and year fixed effects included in each regression though not reported here. The variables *wheat yield* and *maize yield* were instrumented using *drought*.
[1] Natural log

Sensitivity Analyses and Competing Mechanisms

Below I evaluate the sensitivity of my findings to the plausible exogeneity assumption, modeling choices, and a large number of competing mechanisms.

Sensitivity Analyses

I begin by assessing the robustness of my IV regression results to small departures from the strict exogeneity assumption required for those results to be identified. Having discussed these issues theoretically above, I apply the method developed by Conley, Hansen and Rossi (2012) to deal with plausibly—but not strictly—exogenous instruments. In applying this methodology, it is necessary to impose some sort of prior on said departures from strict exogeneity, with the trade-off being that the less precise the prior, the less precise the resulting models' estimates will be. I thus utilize Conley et al's intermediate local-to-zero (LTZ) method, which only requires one to impose a prior on the mean and standard deviation for the parameter measuring the magnitude of the presumed departure from strict exogeneity. In this case, I assume a mean of a zero (i.e., no direct effect) and a standard deviation of 0.1, thus allowing for relatively wide departures from strict exogeneity. However, the LTZ approach relies on particular specifications and a large number of computer simulations. Due to the size of my sample and the complications involved with using grid cell fixed effects under this framework, it was impossible to run LTZ models with available computer resources.

Considering these complications, each LTZ model was estimated on a collapsed sample for the entire 11-year period of analysis. In this sample, a binary indicator for drought, denoting whether a given grid cell experiences drought with one or more standard deviations below the mean of a given cell's precipitation levels, is used as an IV, while all other variables were averaged for the entire period (excluding *conflict*, which was summed). This time-invariant grid cell framework thus nullifies the need for grid cell fixed effects. Additionally, because the LTZ approach requires the inclusion of at least one exogenous variable alongside the endogenous one in the model, all Baseline models include *population* in addition to *wheat yield* and *maize yield*. The results of the Conley, Hansen and Rossi's LTZ estimations presented in Table 2.6 then show that both food indicators are robust to substantive departures from the assumption of strict exogeneity of drought on conflict.

Another methodological concern relates to the structure of my data, which include a large number of units, but a relatively low number of time periods. This

Table 2.6: IV regression models for total number of conflict events per grid cell, LTZ simulations

	Wheat Yield		Maize Yield	
	5) Baseline	**6) Full**	**7) Baseline**	**8) Full**
Wheat yield	261.17***	150.19**	–	–
	(77.48)	(59.96)		
Maize yield	–	–	312.11***	210.58**
			(90.24)	(81.22)
Population[1]	1.259***	-0.752*	0.541	-1.285**
	(0.326)	(0.383)	(0.474)	(0.595)
Conflict (spatial)	–	36.19***	–	35.37***
		(3.327)		(3.139)
Democracy	–	0.406***	–	-0.112
		(0.128)		(0.086)
GDP per capita[1]	–	-2.184**	–	-0.644*
		(0.840)		(0.340)
Constant	-11.85***	20.22**	-6.973*	13.65*
	(3.008)	(9.171)	(3.878)	(7.167)
Observations	6,680	6,429	6,680	6,429
Endogenous variables test	11.69***	7.437***	12.33***	7.174***
Weak instrument F-statistic (clustered SEs)	22.303	9.404	25.56	7.284
Weak instrument F-statistic (i.i.d. SEs)	11.12	5.931	19.59	5.581
R^2	-0.191	0.063	-0.101	0.069
Adjusted R^2	-0.192	0.062	-0.1012	0.068

* indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$ (two-tail test).
Cell values are IV regression coefficient estimates with standard errors clustered by grid-cell in parentheses. The variables *wheat yield* and *maize yield* were instrumented using a collapsed binary version of *drought*.

[1] Natural log

might suggest susceptibility to estimation bias when linear fixed effect models—implying unobserved heterogeneity—are used (Blundell and Bond, 1998). On a related note, the time demeaning operation of fixed effects in these models means that the error terms of the dependent variable and its lag are correlated, causing an inconsistency in such estimator, which is referred to as the "Nickel Bias" (Blundell and Bond, 1998, 128). Although the use of standard IV regressions within panel-time-series data is a standard practice (e.g., Miguel, Satyanath and Sergenti, 2004; Sarsons, 2015), to show that my IV model results are robust to these concerns, I additionally estimate a series of generalized method of moments (GMM) models below (Blundell and Bond, 1998). A key assumption of these GMM models is that the necessary instruments are "internal;" that is, based on lagged values of the instrumented variable(s). The model is accordingly specified as a system of equations, one per time period, where the instruments applicable to each equation differ (in later time periods, additional lagged values of the instruments are available). With the individual fixed effects swept out, a straightforward instrumental variable estimator is available. The system GMM approach also has an advantage over first-differencing GMM models, as the former is much more susceptible to the aforementioned Nickel Bias effects (Blundell and Bond, 1998, 128; 138), and was hence preferred within the context of the present analysis.

Following the procedure established by Blundell and Bond (1998) for using endogenous instruments in dynamic panel data, I estimate system GMM IV models that rely on the past values of yields as instruments for the contemporary effect of yields on conflict. However, to further ensure that these models can claim exogeneity, and considering that the large size of the grid panel suggests a very large number of available lagged instruments and thus overfitting (Arellano, 2003;

Roodman, 2009, 139-140), I rely on deeper lags of the dependent variable, in a manner suggested by past research (Arellano, 2003; Blundell and Bond, 1998; Roodman, 2009, 137). Therefore, in all models reported in Table 2.7 the GMM instruments are the $t-4$ and beyond lags of the dependent variable, *conflict*.

The results of the Blundell and Bond (1998) system GMM models presented in Table 2.7 show that both local yields indicators are statistically robust to departures from the 2SLS framework, although marginally so in the full specification of the *maize yield* model. While the results are not statistically weakened due to the inclusion of a large number of endogenous instruments, Sargan tests do offer evidence of over-identification, even when relying only on deep DV lags, implying that endogeneity may remain a concern within these GMM models. While this can be explained by the sheer size of the grid panel (10,674 cells), by providing an additional way of instrumenting the effect of food on conflict, these GMM models nevertheless show that the relationship between local yields is positive, which complements the IV regressions and LTZ models used previously.

Competing Mechanisms

Having shown that the finding presented in Table 2.4 are generally robust to modeling choices, I now turn to empirically evaluating a large number alternative mechanisms that could explain the main results.

One of the most robust explanations to the onset of conflict connects low development and economic inequalities to conflict frequency (Blattman and Miguel, 2010; Fearon and Laitin, 2003). Considering that such underdeveloped regions are also more susceptible to limitations on food access and availability (Kastner et al., 2012), low development, economic inequality, and limitations of food are likely to

Table 2.7: GMM IV regression models for total number of conflict events per grid cell, 1998-2008

	Wheat Yield		**Maize Yield**	
	9) Baseline	**10) Full**	**11) Baseline**	**12) Full**
Wheat yield	0.610***	0.231**	–	–
	(0.174)	(0.108)		
Maize yield	–	–	2.257***	0.309*
			(0.530)	(0.165)
Conflict (lag)	0.382***	0.781***	0.381***	0.780***
	(0.090)	(0.087)	(0.089)	(0.087)
Conflict (spatial)	–	-0.223*	–	-0.220*
		(0.127)		(0.127)
Population[1]	–	-0.0003	–	-0.001
		(0.002)		(0.002)
Democracy	–	0.001	–	-0.0001
		(0.001)	(0.001)	
GDP per capita[1]	–	0.002	–	0.003
		(0.003)		(0.003)
Observations	72,169	68,160	72,169	68,160
Sargan test	73.69***	612.47***	75.436***	613.03***
DF	(39)	(43)	(39)	(43)
R^2	0.082	0.088	0.083	0.088

* indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$ (two-tail test).
Cell values are IV regression coefficient estimates with robust standard errors in parentheses.
GMM instruments for all models are the $t - 4$ and beyond lags of *conflict*.
[1] Natural log

be highly correlated. From this perspective, grid cells with lower economic activity are likely to have more unemployment, more disadvantaged individuals, and hence suffer from more conflict, independently of variation in local yields.

To this end, Model 13 in Table 2.8 replicates the Full IV analysis with the inclusion of an annual cell-level economic development indicators, *nighttime light*, which measures annual nighttime light emissions in a given cell as a proxy of local development, as used by past studies (see, e.g., Chen and Nordhaus, 2011; Koren and Sarbahi, Forthcoming; Elvidge et al., 2014). This variable measures the annual (calibrated) average of nighttime light emissions at the 0.5 degree grid cell resolution. It captures average visible (i.e., cloud free and stable) nighttime light emission obtained from the DMSP-OLS Nighttime Lights Time Series Version 4 (Average Visible, Stable Lights, & Cloud Free Coverages).

Original DMSP data were collected by US Air Force Weather Agency, and processed by the NOAA's National Geophysical Data Center (see, e.g., Elvidge et al., 2014). While numerous nighttime light measures are available, the indicator I chose to employ for approximating localized development was calibrated using values from Elvidge et al. (2014) to account for differences between data from different satellites and sensor decay over time, making these measures especially useful for time-series analysis (Tollefsen et al., 2012). Values are standardized to be between zero and one, where one is the highest observed value in the entire time-series, and zero is the lowest for the years 1992-2012, and aggregated to the 0.5 degree grid cell level.

As can be observed, the variables *wheat yield* and *maize yield* maintain their sign and significance across all models, suggesting that their impact is not (only) the result of low development levels and inequalities. Moreover, in addition to illustrating the validity of this mechanism by the process of elimination—i.e. by empirically accounting for a variety of alternative mechanisms— Figure 2.5 further highlights the interactions between economic inequality, food resources, and conflict. These plots report nonparametric regressions, i.e. regressions where the predictor does not take a predetermined form but is constructed according to information derived from the data (see, e.g., Fan, 1992). The shape of the functional relationships between the response (dependent) and the explanatory (independent) variables in these models are thus not predetermined, but can be adjusted to capture unusual or unexpected features of the data.

As Figure 2.5 shows, nonparametric regression plots—which do not enforce a modeling structure on the data and hence provide a more flexible method of visualizing relationships between different factors—show the correlations of local yields and conflict in respect to economic development as approximated using nighttime light levels. As shown, conflict occurs more frequently in cells with more yields but relatively low levels of productivity and development, where—based on anecdotal evidence at least—limitations on food access are more likely (Roncoli, Ingram and Kirshen, 2001).

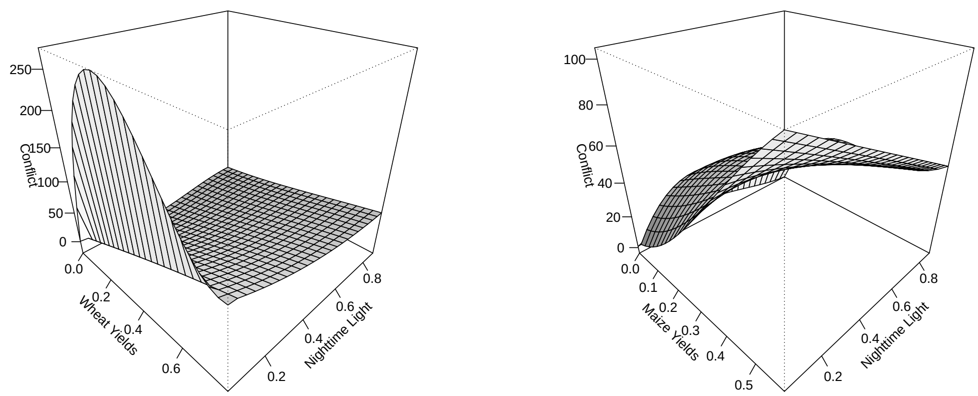


Figure 2.5: Nonparamteric regression plots of annual nighttime light emissions on violent conflict over the range of (left) wheat yields and (right) maize yields by grid cell in Africa, 1998-2008.

Model 14 in Table 2.8 examines whether the observed effects of the crop yield variables is driven by abundance of lucrative resources such as oil and oil exports (Ross, 2011), which previous research connected to higher frequency (e.g., Bannon and Collier, 2003; Blattman and Miguel, 2010). The variable *oil production* approximates annual oil production by country (in metric tones), starting in 1932. The variable *gas production* measures annual gas production by country (also in metric tones), starting in 1955. For 1970 to 2000, these data originally obtained from the World Bank's "Wealth of Nations" database, while 2000–2011 data are taken from the US Energy Information Administration website (Ross, 2011). The effect of localized food production remains positive and significant in these models, suggesting that the availability of other profitable natural resources is not driving the results.

Third, some scholars have highlighted the potential effect of food imports and food aid on conflict (e.g., Bellemare, 2015; Nunn and Qian, 2014). From this perspective, higher levels of food imports and food aid might increase competition between armed groups over expropriating these resources, and hence explain the pattern observed in Table 2.4. To account for the impact of food and agricultural imports more broadly, as well as total aid, Model 15 includes three additional controls—*food imports* and *agricultural imports*, *aid*, all taken from World Bank (2012). The first variable, *food imports*, measures the annual total share (in percents) of a given country's total food merchandise imports according to the World Bank (2012). The second variable *agricultural imports*, measures raw materials imports (excluding fuel, fertilizer, minerals, and ores), and again operationalized as the annual share of total imports during the same calendar year according to the World Bank (2012). Finally, the variable *aid* is operationalized as the annual net of repayments involving all official development assistance (ODA) and other official aid flows (in constant 2008 USD) provided to a given country (World Bank, 2012).

Although the variable *agricultural imports* has a statistically significant effect across all models and *food imports* in all models excluding one, the inclusion of these variables does not diminish the sign and significance of *wheat yield* and *maize yield*. The impact of *local* food yields on the propensity of conflict is again shown to be independent of that of other factors, in this case agricultural and aid dependencies at the national level.

Fourth, recall that my dependent variable incorporates all conflict types and related developments occurring within a given cell during a given year, with or without casualties. A competing explanation might be that the number of conflicts without casualties "inflates" the variable *conflict*, thus affecting the results. To address this concern, Model 16 re-estimates the Full analyses on a dependent variable that captures only violent incidents, i.e., recorded events at the village level with at least one combatant or civilian fatality. This variable, *violent conflict*, as well as its one-year lag were operationalized from the same ACLED Version 6 dataset (Raleigh et al., 2010), where only incidents that included at least one combatant or noncombatant fatality were counted. Like all other conflict variables used in the main and sensitivity analyses, this variable includes only recorded events whose geographic precision was the village—and not district, province, or country—level. The coefficients of both *wheat yield* and *maize yield* maintain their sign, significance, and size (within one order of magnitude), suggesting that the the findings are robust to inclusion of nonviolent conflict events within the dependent variable.

Fifth, previous research has drawn strong linkages between ethnic enmities and localized political violence (e.g., Fjelde and Hultman, 2014). To evaluate whether the primary findings were the result of such ethnic enmities, Model 17 in Table 2.9 includes two additional controls. The first, *ethnic diversity*, is operationalized as a count of the number of politically relevant ethnic groups settled in a particular cell during a given year (Wucherpfennig et al., 2011). This indicator thus accounts for the number of distinct ethnic groups found within each individual cell, and control for the possibility that conflict was the result of preexisting inter-ethnic divisions. The second variable, *territorial change*, is a binary variable denoting a whole or part of a grid cell exchanged hands between different noncombatants during a fiven year (Raleigh et al., 2010). This variable accounts for some persistent enmities between different groups and the possibility that some armed actors might initiate conflict or move into these regions to recover territories previously lost. As Model 17 shows, the coefficients of both *wheat yield* and *maize yield* maintain their sign, significance, and size.

Sixth, recall that my argument does not suggest that scarcity never impacts conflict, but rather that—on average—violence would be more frequent in areas with abundant food. To provide a more empirically thorough evaluation of scarcity's role in driving conflict, Model 18 incorporates two additional controls, *temperature* and *temperature (lag).* This variables measure the average and lagged average annual temperature, respectively, in a given cell (in Celsius) (Fan and Van den Dool, 2008; Tollefsen et al., 2012) to account for the effect of heat waves on local scarcity, and correspondingly, conflict. Model 19 adds two production index indicators to the model, capturing production levels of meat and cereals, respectively (Food and Agricultural Organization of the United Nations, 2016). The FAO indices of agricultural production show the relative level of the aggregate volume of agricultural production for each year in a given country (normalized per capita) in comparison with the base period 1999-2001. These two variables are based on the sum of price-weighted quantities of meat products and cereals, respectively, produced after deductions of quantities used as seed and feed (also weighted against the same base period). The resulting aggregate variables, *meat prod. index* and Cereal prod. index, thus capture disposable production for immediate or long-term consumption (i.e., not as seed or feed). Model 20 then incorporates both temperature measures and both indexes.

As evidenced by Table 2.9, doing so does not diminish the sign or significance of *wheat yield* and *maize yield*. This, again, lends support to the argument that, at least at the local level, on average, food abundance impacts conflict. Additionally, the coefficients signs of *temperature* and *temperature (lag)* change from positive to negative as one moves from the wheat models to the maize models. Considering that R^2 scores suggest that both wheat models are preferred to their maize counterparts, it might be that conflict is more frequent in regions that previously experienced both higher yields and higher temperatures, although these results are far from definite. Alternatively, wheat might be simply more sensitive to higher temperatures.

Interestingly, when the cereal and meat production indexes (obtained from Food and Agricultural Organization of the United Nations, 2016) are added to the models (for countries and years for which information is available), the former's effect is positive and significant, while the latter's effect is negative and significant. These results can help reconcile some of this paper's seemingly-counterintuitive findings with previous research that emphasizes the role of scarcity. For instance, Maystadt and Ecker (2014) find that droughts induce higher food prices, which in turn increases localized frequency of conflict. In contrast, Table 2.4 illustrates that when the same instruments are used for cereals, the results are the opposite. Interestingly, in both Model 19 and 20, country-level food production indexes exhibit the same relationship: cereal production has a positive and significant relationship with conflict frequency, while meat production is negative and significant. This suggests that future research should focus not necessarily on whether scarcity vs.

abundance drives conflict, but rather on the distinct relationships exhibited by different food resource types with respect to conflict.

Seventh, to address the concern that rebel groups might be more dependent on locally grown food than official state forces, Model 21 in Table 2.10 reestimates the Full specifications, where the dependent variable includes only conflicts waged by official state forces. The dependent variable, *military conflict*, as well as its one-year lag, was operationalized as the annual number of all conflict events in a given grid cell—with and without fatalities—that involved official military forces. In these models, the dependent variable (and its lag) were operationalized as the annual number of all conflict events—with and without fatalities—that involved military forces in given grid cell. The results are robust to this choice of DV, suggesting that—as previous research (e.g., Koren and Bagozzi, 2016) shows—abundance has a noticeable impact even on regular state forces, which are generally considered better organized and well-supported.

Eighth, note that my sample includes a relatively large number of cells with zero values or missing informations, which might affect the results. To address these concerns, I first re-estimate the Full models on two subsamples that include only grid cells where some wheat or maize, respectively, are grown in Model 22. I then repeat these analysis using a subsample that includes only grid cells that experienced conflict as some point during the period analysis in Model 23. As can be observed in both sets of analyses, the coefficients of *wheat yield* and *maize yield* maintain their sign, size, and significance, suggesting that the findings are not driven by a high number of zero values or missing information on conflict events. Ninth, considering that some studies suggest larger countries are also more likely to suffer from protracted conflict (e.g., Fearon and Laitin, 2003), Model 24 re-estimates the Full specifications on a sample consisting solely of countries whose geographic size is bellow the 75% percentile of all African countries.

Table 2.11 accounts for possible biases that might be caused by the distribution of the dependent variable or the choice of the unit of analysis. To this end, Model 25 re-estimates the full specification using a logged version of the dependent variable (and its lag) to verify that the effect of *wheat yield* and *maize yield* is not driven by the range of values on *conflict* ($0 \Leftrightarrow$ 344 annual incidents). Model 26 then re-estimates the Full specifications on a sample where the top one percent of all values (including zero values, to make this sensitivity test even more robust) on *wheat yield* and *maize yield* was removed from each model, respectively, as to account for the effect of outliers.

Next, considering that political violence measured at the 0.5 $\circ$ x 0.5 $\circ$ fine-scale level might exhibit higher levels of spatial and serial correlations besides the regressors in equations 1 and 2 in the main paper, Model 27 re-estimates the Full IV models, where standard errors are clustered at the higher, province level of aggregation. Finally, to account for both observed and unobserved annual country-level factors, Model 28 re-estimates the Full model with the inclusion of country $\times$ year fixed effects. Note that this procedure is very likely to generate Type II errors, and indeed, the model issues a warning that the standard errors are likely to be too high, which did not happen with any of the other (numerous) models estimated in this chapter. Nevertheless, the results are robust to the inclusion of country $\times$ year fixed effects in the maize model, although the wheat model drops out of significance ($p = 0.17$).

Finally, recall that the *drought* variable used to instrument food yields is an ordinal measure of different degrees of drought severity. To illustrate that the effect of drought as an instrument for local food yield is robust to more penalizing thresholds of negative rainfall shocks, several alternative binary IVs are used to instrument the average LATE of *wheat yield* and *maize yield* on *conflict* in Table 2.12 below. The first alternative instrument used in Model 29, *any drought*, is a binary variable operationalized as grid cell years that experienced drought levels of 1 or more standard deviations below average precipitation level, zero otherwise. The instrument used in Model 30, *severe drought*, is a binary variable operationalized as grid-cell years that experienced drought levels of 1.5 or more standard deviations below average precipitation level, zero otherwise. The instrument used in Model 31, *extreme drought*, is a binary variable operationalized as grid-cell years that experienced the worst drought levels of 2.5 standard deviations below average precipitation level, zero otherwise. The sign, size, and significance of each local food yield's coefficient remains practically unchanged, even when droughts are operationalized using these different negative rainfall shock thresholds. Indeed, across all models, the coefficients of both *wheat yield* and *maize yield* maintain their sign, significance, and size within a series of robustness specifications that includes these additional controls.

Discussion and Conclusion

The theoretical argument and empirical analyses presented in this chapter suggest that agricultural regions experience relatively high levels of violent conflict that are, to a large extent, driven by the type and amount of food resources produced there. These findings diverge from current conceptualizations in mainstream literature, which frequently attribute conflict to food shortages (e.g., Burke et al., 2009; Maystadt and Ecker, 2014). This chapter theorizes and provides empirical evidence to show that scarcity-based explanations are insufficient in explaining localized conflict over food resources, their potential validity notwithstanding. Moreover, the evidence that the instrument *drought* have a significant and *negative* association with production lends additional support to this argument by showing that conflict is significantly less likely during drought, presumably because, as Adano et al. argue, "in dry season times of relative scarcity...people reconcile their differences and cooperate" (2012, 77).

Importantly, while the theoretical argument and corresponding empirical analysis presented here draw and test linkages between conflict and food abundance, thus isolating the validity of the broad group of mechanisms responsible for these linkages, they do not test the relative importance of some specific mechanisms. For instance, one important implication of the value different actors place on food resources is that denying these resources from one's rivals can be a useful tactic and an especially powerful weapon not only in localized conflict but also as a macrolevel strategy designed to win a total war (Messer, 2009). Indeed, it is possible that this "preemptive" exposition explains a significant number of the conflict incidents occurring in food resources abundant regions. In the next chapter I turn

Table 2.8: IV regression models for total number of conflict events per grid cell, additional robustness models

	13) Development		14) Resources		15) Aid		16) Violent	
	Wheat Yield	**Maize Yield**	**Wheat Yield**	**Maize Yield**	**Wheat Yield**	**Maize Yield**	**Wheat Yield**	**Maize Yield**
Wheat yield	83.44***	–	78.50***	–	36.09***	–	25.04***	–
	(26.010)		(24.74)		(12.50)		(7.718)	
Maize yield	–	204.65***	–	178.79***	–	79.85***	–	61.31***
		(62.74)		(54.74)		(26.93)		(18.48)
Nighttime light[1]	-19.04***	-7.945	–	–	–	–	–	–
	(6.154)	(5.185)						
Oil production[1]	–	–	0.006	0.025***	–	–	–	–
			(0.004)	(0.009)				
Gas production[1]	–	–	-0.133***	-0.229***	–	–	–	–
			(0.037)	(0.062)				
Food imports	–	–	–	–	0.011***	0.003	–	–
					(0.004)	(0.003)		
Agricultural imports	–	–	–	–	0.006**	0.006**	–	–
					(0.003)	(0.003)		
Aid[1]	–	–	–	–	0.698**	-0.036*	–	–
					(0.020)	(0.021)		
DV (lag)	0.200**	0.205**	0.200**	0.204**	0.423***	0.426***	0.353**	0.357***
	(0.084)	(0.084)	(0.084)	(0.084)	(0.066)	(0.066)	(0.052)	(0.052)
Conflict (spatial)	0.341***	0.435***	0.328***	0.393***	0.076**	0.099**	0.067***	0.095***
	(0.086)	(0.110)	(0.083)	(0.099)	(0.038)	(0.041)	(0.019)	(0.024)
Population[1]	-0.892***	-2.768***	-0.796***	-2.414***	-0.408**	-1.464***	-0.353***	-0.918***
	(0.241)	(0.798)	(0.228)	(0.697)	(0.159)	(0.0458)	(0.093)	(0.243)
Democracy	-0.031***	0.008	-0.038***	-0.007	-0.035***	-0.018*	-0.011**	-0.001
	(0.011)	(0.013)	(0.011)	(0.010)	(0.013)	(0.010)	(0.005)	(0.005)
GDP per capita[1]	-0.041	-0.333	0.084	-0.165	-0.042**	0.346	-0.030	-0.116
	(0.180)	(0.246)	(0.171)	(0.217)	(0.293)	(0.242)	(0.064)	(0.076)
Obs.	68,160	68,160	68,160	68,160	49,362	49,362	68,160	68,160
End. variables	10.29***	10.64***	10.07***	10.67***	8.34***	8.794***	10.53***	11.01***
WI F-stat. (CSEs)	7.204	7.678	6.354	7.712	5.518	7.846	8.372	8.983
WI F-stat. (ISEs)	27.48	13.08	24.30	13.55	22.24	14.05	31.84	15.30
R^2	0.353	0.265	0.361	0.305	0.588	0.573	0.483	0.442
Adj. R^2	0.285	0.188	0.294	0.232	0.540	0.524	0.429	0.384

* indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$ (two-tail test).

Cell values are IV regression coefficient estimates with standard errors clustered by grid-cell in parentheses. Grid cell and year fixed effects included in each regression though not reported here. The variables *wheat yield* and *maize yield* were instrumented using *drought*.

[1] Natural log

Table 2.9: IV regression models for total number of conflict events per grid cell, additional robustness models (cont.)

	17) Ethnic		18) Temperature		19) Production		20) Scarcity	
	Wheat Yield	**Maize Yield**	**Wheat Yield**	**Maize Yield**	**Wheat Yield**	**Maize Yield**	**Wheat Yield**	**Maize Yield**
Wheat yield	75.59***	–	96.10***	–	35.86***	–	45.36***	–
	(23.79)		(30.47)		(13.84)		(17.11)	
Maize yield	–	186.38***	–	193.48***	–	143.30**	–	132.70***
		(57.97)		(58.64)		(57.77)		(50.39)
Ethnic diversity	0.086***	0.286***	–	–	–	–	–	–
	(0.027)	(0.074)						
Terr. change	5.859***	5.918***	–	–	–	–	–	–
	(0.826)	(0.842)						
Temperature	–	–	0.178***	-0.129***	–	–	0.219***	-0.283**
			(0.057)	(0.047)			(0.073)	(0.088)
Temperature (lag)	–	–	0.049*	-0.151***	–	–	-0.039	-0.283***
			(0.026)	(0.057)			(0.027)	(0.099)
Cereal prod. index	–	–	–	–	0.001**	0.001**	0.001**	0.001**
					(0.0005)	(0.0005)	(0.0005)	(0.0005)
Meat prod. index	–	–	–	–	-0.006***	-0.007***	-0.006***	-0.007***
					(0.002)	(0.003)	(0.002)	(0.002)
DV (lag)	0.182**	0.186**	0.210**	0.215**	0.415***	0.418***	0.418***	0.421***
	(0.080)	(0.080)	(0.090)	(0.090)	(0.073)	(0.074)	(0.077)	(0.077)
Conflict (spatial)	0.182**	0.186**	0.345***	0.456***	0.104***	0.162***	0.108**	0.179***
	(0.080)	(0.080)	(0.091)	(0.117)	(0.042)	(0.006)	(0.046)	(0.060)
Population[1]	-0.675***	-2.360***	-1.031***	-2.488***	-0.490***	-2.122***	-0.718***	-1.611***
	(0.211)	(0.714)	(0.279)	(0.718)	(0.198)	(0.793)	(0.245)	(0.582)
Democracy	-0.022**	0.010	-0.034***	0.007	-0.036*	-0.019	-0.043**	-0.016
	(0.011)	(0.012)	(0.011)	(0.013)	(0.019)	(0.016)	(0.021)	(0.016)
GDP per capita[1]	-0.033	-0.312	-0.087	-0.285	0.847***	1.931***	0.829***	2.183***
	(0.165)	(0.237)	(0.194)	(0.240)	(0.285)	(0.665)	(0.281)	(0.714)
Obs.	67,755	67,755	66,007	66,007	35,936	35,936	34,254	34,254
End. variables	10.09***	10.34***	9.951***	10.89***	6.714***	6.157**	7.031***	6.934***
WI F-stat. (CSEs)	6.269	6.665	5.364	7.656	6.015	3.664	3.912	3.871
WI F-stat. (ISEs)	24.019	11.40	18.89	13.54	22.48	6.908	13.528	8.109
R^2	0.396	0.323	0.327	0.283	0.593	0.534	0.575	0.547
Adj. R^2	0.333	0.253	0.256	0.207	0.552	0.488	0.532	0.501

* indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$ (two-tail test).

Cell values are IV regression coefficient estimates with standard errors clustered by grid-cell in parentheses. Grid cell and year fixed effects included in each regression though not reported here. The variables *wheat yield* and *maize yield* were instrumented using *drought*.

[1] Natural log

Table 2.10: IV regression models for total number of conflict events per grid cell, additional robustness models (cont.)

	21) Military Conflict		22) Planted Cells		23) Conflict Cells		24) Large Count.	
	Wheat Yield	**Maize Yield**	**Wheat Yield**	**Maize Yield**	**Wheat Yield**	**Maize Yield**	**Wheat Yield**	**Maize Yield**
Wheat yield	62.15***	–	77.42***	–	226.55***	–	87.81***	–
	(20.38)		(26.22)		(77.31)		(26.19)	
Maize yield	–	152.44***	–	191.52***	–	643.08***	–	223.02***
		(49.09)		(59.56)		(227.85)		(63.93)
DV (lag)	0.090	0.091	0.204**	0.207**	0.197**	0.213**	0.177	0.183**
	(0.073)	(0.074)	(0.100)	(0.089)	(0.085)	(0.085)	(0.088)	(0.089)
Conflict (spatial)	0.297***	0.366***	0.383***	0.435***	0.351***	0.643***	0.492***	0.729***
	(0.076)	(0.096)	(0.114)	(0.114)	(0.110)	(0.193)	(0.128)	(0.185)
Population[1]	-0.689***	-2.093***	-0.991***	-2.665***	-4.422***	-13.84***	-1.044**	-3.354***
	(0.193)	(0.631)	(0.302)	(0.802)	(1.299)	(4.388)	(0.270)	(0.903)
Democracy	-0.015**	0.014	-0.042***	0.006	-0.085***	0.020	-0.078***	-0.052
	(0.007)	(0.010)	(0.014)	(0.012)	(0.029)	(0.042)	(0.025)	(0.905)
GDP per capita[1]	-0.099	-0.314	-0.445*	-0.459*	-0.291	-1.132	-0.005	0.241
	(0.161)	(0.218)	(0.256)	(0.263)	(0.549)	(0.888)	(0.213)	(0.227)
Obs.	68,160	68,160	50,461	65,367	19,450	19,450	47,613	47,613
End. variables	9.303***	9.644***	8.722***	10.34***	8.587***	7.966***	11.24***	12.17***
WI F-stat. (CSEs)	8.372	8.943	8.300	9.430	3.963	2.963	7.920	10.29
WI F-stat. (ISEs)	31.84	15.23	29.61	16.17	7.961	5.532	29.63	19.45
R^2	0.170	0.069	0.353	0.280	0.083	-0.077	0.310	0.252
Adj. R^2	0.084	-0.028	0.285	0.206	-0.014	-0.190	0.240	0.177

* indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$ (two-tail test).

Cell values are IV regression coefficient estimates with standard errors clustered by grid-cell in parentheses. Grid cell and year fixed effects included in each regression though not reported here. The variables *wheat yield* and *maize yield* were instrumented using *drought*.

[1] Natural log

[2] This variable is only available for the years 1998-2007

Table 2.11: IV regression models for total number of conflict events per grid cell, additional robustness models (cont.)

	25) Logged DV		**26) Outliers Removed**		**27) Province SEs**†		**28) Count. × Year FEs** ‡	
	Wheat Yield	**Maize Yield**	**Wheat Yield**	**Maize Yield**	**Wheat Yield**	**Maize Yield**	**Wheat Yield**	**Maize Yield**
Wheat yield	4.239**	–	187.17***	–	83.53**	–	423.41	–
	(1.861)		(57.68)		(36.76)		(314.47)	
Maize yield	–	10.37**	–	249.13***	–	204.74**	–	96.45**
		(4.476)		(77.28)		(94.83)		(46.45)
DV (lag)	0.659***	0.662***	0.203**	0.209**	0.201**	0.206**	0.204***	0.207***
	(0.012)	(0.012)	(0.085)	(0.085)	(0.084)	(0.084)	(0.066)	(0.243)
Conflict (spatial)	0.015**	0.019***	0.349***	0.449***	0.343***	0.436***	0.188**	0.228***
	(0.007)	(0.007)	(0.088)	(0.114)	(0.105)	(0.144)	(0.082)	(0.068)
Population[1]	-0.101***	-0.196***	-0.774***	-2.758***	-0.877***	-2.762**	0.636	0.505**
	(0.018)	(0.052)	(0.226)	(0.798)	(0.332)	(1.078)	(0.413)	(0.243)
Democracy	-0.005***	-0.003***	-0.039***	0.010	-0.032**	0.007	–	–
	(0.001)	(0.001)	(0.012)	(0.013)	(0.013)	(0.021)		
GDP per capita[1]	0.012	-0.003	-0.115	-0.612**	-0.048	-0.336	–	–
	(0.013)	(0.017)	(0.191)	(0.305)	(0.300)	(0.406)		
Obs.	68,160	68,160	67,439	67,453	68,160	68,160	70,937	70,937
End. variables	5.186**	5.365**	10.53***	10.39**	5.163**	4.661**	1.813	4.319**
WI F-stat. (CSEs)	8.361	8.979	9.611	9.583	1.951	1.342	0.756	19.20
WI F-stat. (ISEs)	31.81	15.31	30.09	16.08	31.84	15.26	1.034	29.26
R^2	0.661	0.647	0.345	0.276	0.351	0.264	0.114	0.510
Adj. R^2	0.626	0.610	0.276	0.200	0.284	0.187	0.013	0.454

* indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$ (two-tail test).

Cell values are IV regression coefficient estimates with standard errors clustered by grid-cell in parentheses unless noted otherwise. Grid cell and year fixed effects included in each regression though not reported here. The variables *wheat yield* and *maize yield* were instrumented using *drought*.

† Standard errors clustered by province/state in parentheses.

‡ Model warning: Standard errors may be too high.

[1] Natural log

Table 2.12: IV regression models for total number of conflict events per grid cell, additional robustness models, alternative drought thresholds

	29) Low Threshold †		30) Medium Threshold ‡		31) High Threshold §	
	Wheat Yield	**Maize Yield**	**Wheat Yield**	**Maize Yield**	**Wheat Yield**	**Maize Yield**
Wheat yield	78.66***	–	82.06***	–	92.64***	–
	(23.65)		(28.52)		(31.32)	
Maize yield	–	208.01***	–	198.67***	–	203.38***
		(60.95)		(67.27)		(68.54)
DV (lag)	0.201**	0.206**	0.201**	0.206**	0.201**	0.206**
	(0.084)	(0.084)	(0.084)	(0.084)	(0.084)	(0.084)
Conflict (spatial)	0.343***	0.438***	0.343***	0.433***	0.343***	0.435***
	(0.086)	(0.109)	(0.087)	(0.111)	(0.087)	(0.112)
Population[1]	-0.865***	-2.796***	-0.873***	-2.700***	-0.873***	-2.749***
	(0.233)	(0.776)	(0.240)	(0.836)	(0.240)	(0.855)
Democracy	-0.032***	0.008	-0.032***	0.006	-0.032***	0.007
	(0.011)	(0.013)	(0.011)	(0.013)	(0.011)	(0.013)
GDP per capita[1]	-0.044	-0.322	-0.047	-0.326	-0.047	-0.334
	(0.180)	(0.245)	(0.181)	(0.249)	(0.181)	(0.250)
Obs.	68,160	68,160	68,160	68,160	68,160	68,160
End. variables	11.06***	11.65***	8.279***	8.724***	8.750***	8.805***
WI F-stat. (CSEs)	8.300	8.778	5.692	6.668	7.533	7.601
WI F-stat. (ISEs)	35.23	14.50	22.32	10.97	20.43	12.21
R^2	0.360	0.259	0.354	0.274	0.334	0.266
Adj. R^2	0.293	0.182	0.287	0.198	0.264	0.190

* indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$ (two-tail test).

Cell values are IV regression coefficient estimates with standard errors clustered by grid-cell in parentheses. Grid cell and year fixed effects included in each regression though not reported here.

† The variables *wheat yield* and *maize yield* were instrumented using *any drought*

‡ The variables *wheat yield* and *maize yield* were instrumented using *severe drought*

§ The variables *wheat yield* and *maize yield* were instrumented using *extreme drought*

[1] Natural log

to evaluate the role of this preemptive mechanism on conflict in Africa using a combination of a formal model and a corresponding statistical strategic model to test the formal theory's implications.

Chapter 3: Food Security and Strategic Preemptive Conflict

In Chapter 1, I identified a mechanism that I termed *possessive conflict*, which stipulates that armed actors actively fight over areas with more food to guarantee long term operations and community resilience to food shortages, or move into these areas during ongoing war to sustain their operations. I then further developed and evaluated this argument empirically in Chapter 2 using different methodological approaches, under the broad assumption that we should expect to see different types of conflict occurring more frequently during years of *abundance*, not scarcity. However, I also recognized that this conflict pattern has several potential explanations, the need to possess food resources (during ongoing war or otherwise) being only one of which. While my models and sensitivity analyses include a variety of variables and specifications designed to control for these alternatives, these approaches cannot adequately account for sequential interactions resulting from strategic behaviors of different actors in response to other the behaviors of other grous.

In this chapter I focus on one such strategic interactions and its role in generating local conflict over food resources. Understanding how this mechanism operates is important given that evidence from countries as diverse as Uganda (Mkutu, 2001), the Democratic Republic of the Congo (Vlassenroot and Raeymaekers, 2008), Peru (Gitlitz and Rojas, 1983), and India (Wischnath and Buhaug, 2014) suggests that conflict dynamics are closely associated with strategic interactions over food resources. As I mentioned in the Chapter 1, the focus on scarcity alone cannot predict where conflict over food will arise *within* the state. For example, a close examination of violent conflict data at the *disaggregated* within-country "grid-cell year" level in Africa (Raleigh et al., 2010),[1] reveals that violent conflict *predominately* arises in regions where at least some food is grown (92% of all incidents).[2] Again, this empirical evidence counter-intuitively suggests that, at the local level, violent conflict is associated with food resource *abundance*, and not scarcity. Fitting explanations for the relationship between food and conflict should therefore account for how food resource abundance, in addition to food scarcities, affects local conflict frequency (Koren and Bagozzi, 2016; Butler and Gates, 2012; Adano et al., 2012).

What impact does food security have on patterns of conflict within developing states? Does increasing local food security levels exacerbate or help to quell violence in these areas? To answer these questions, the present chapter advances a complementary explanation to scarcity-centric theories, which emphasizes the strategic incentives of actors not only to secure food resources, but also to *prevent* them from being consumed by others. To achieve strategic advantage, some

[1]I.e., as described in Chapters 1 and 2, "cells" of approximately 55km x 55km around the equator (Tollefsen et al., 2012). Data on all staple food crops was estimated for the year 2000 (Ramankutty et al., 2008).

[2]The reader can also refer back to Table 1.1 from Chapter 1, which illustrates that these correlations are not unique to the ACLED dataset coded by Raleigh et al. (2010), and persist across different datasets and conceptualizations of political violence.

groups might seek to cut off the supply of other armed actors in order to weaken them. This incentive should give rise to violence not only between rebel and government troops, but also between different ethnic communities (Adano et al., 2012; O'Loughlin et al., 2012; Bagozzi, Koren and Mukherjee, 2017). In the developing world, where the majority of armed groups are unlikely to receive regular logistic support (Henk and Rupiya, 2001) and must rely on the local population for food, such a possibility is especially likely.

Reducing rival groups' access to food resources is a powerful strategy to increase strength and guarantee survival during ongoing war, as being deprived of food support significantly reduces an enemy group's fighting ability (Hendrix and Brinkman, 2013). When an organization—be it the military, a rebel group, or an ethnic militia—has access to more local food resources, it can easily recruit individuals and use income from agriculture to purchase weapons (Jaafar and Woertz, 2016; Crost and Felter, 2016). Most importantly, because the majority of armed actors in the developing world must frequently rely on locally-grown food to support their operations, by securing access to such resources an armed actor can operate for longer periods of time and venture further away from its base of operations, increasing its durability. Local food resources are therefore vital to this group and its chances of victory during ongoing war. Correspondingly, to increase its probability of winning a war, the enemy might seek to *preemptively* conquer areas that have more food resources to weaken its opponent. In doing so, it deprives the first group of these essential resources, thus reducing its durability, fighting capability, and size. This in turn will push the first group to stage stronger resistance in these food abundant areas to guarantee continued availability of food resources.

Importantly, theories of conflict rarely if ever incorporate the active roles of civilians, despite the fact that the latter's behavior might influence patterns of political violence (see, e.g., Valentino, 2004; Kalyvas, 2006). Moreover, especially when food resources are concerned, civilians are a crucial actor. The amount of food grown and available for the taking in a given region is a function of natural factors such as climate and soil, but perhaps most importantly of the civilian producers' choices. These choices include not only what types of food to grow, subject to environmental concerns (e.g., cereals, perishables, or livestock), but also whether to provide food to the different warring sides, and if so how, and how much.

Accordingly, I develop the argument presented in this chapter in three phases. First, I derive a formal model to show how food security concerns affect the strategic calculi of (i) the first group, or defense forces, (ii) the second group, or raiders, and (iii) the civilian producers that provide local food support to the defense forces. This model posits that when the local civilians increase their level of food support, they correspondingly increase the probability that the defense forces will win in combat. Moreover, this level of support cannot be known to the raiders in advance. In equilibrium, the raiders anticipate that if more food support is available to the defense forces, their own chances of victory will diminish. The implication is that above a certain probability threshold of the defense forces' victory, the possibility of high food support levels becomes a grave threat. I find that in the model, this incentivizes the raiders to *preemptively* target regions with more food resources in order to cut the defense forces off from these sources of support, and increase their (the raiders') overall probability of victory. Moreover, this formal analysis provides a set of comparative statics that show when the civilian producers are more likely to increase their level of food support in anticipation of this possibility, which makes it more likely that the defense forces will defeat the raiders. I then corroborate my formal model's predictions on high resolution data on conflict and local food production for the years 1998-2008 (Ray et al., 2012; Ramankutty et al., 2008) using a *statistical strategic* model that corresponds to the formal model's derivations. Finally, I use the model to forecast conflict on out-of-sample data for 2009-2010.

Overall, the combined theoretical-empirical model developed in this chapter provides new and nuanced evidence that locally-grown food resources have a strong influence on the strategic calculi of different groups, which generates intensified *pre-emptive* competition over areas with more food resources. Specifically, I show that raiders strategically attack local communities where more access to food resources exists, while higher availability of food also makes a response by defense forces more likely.

Background Discussion

As mentioned in Chapters 1 and 2, the notion that climatic variability affects armed conflict has received much consideration in recent years (Burke et al., 2009; Bagozzi, Koren and Mukherjee, 2017). On the other hand, an increasing number of studies that focus on the *subnational* level now emphasize that *within* scarcity-prone countries, conflict might be more likely to arise in areas with *more* food resources (e.g., Koren and Bagozzi, 2016; Butler and Gates, 2012; Adano et al., 2012). These studies focus on the importance of locally grown resources to maintaining and improving the fighting capacity of different groups in many (rural) regions of the developing world.

Despite the valuable insights into the motivations governing armed actors' imperatives to secure food resources by violent means provided by the studies discussed above and the analyses conducted in Chapter 2, we are still missing an interactive model that (i) is focused on *food resources* (rather than environmental conditions or production and price shocks); and (ii) explains when strategic interactions around food-related concerns shape broader conflict patters, between communities as well as between different armed actors. To explain these interactions and the trend, shown in Chapter 2, that violent conflict concentrates in areas with more food crops, I design my model around the competition over food resources. In this context, food (in)security relates to the (in)ability of actors, armed groups and communities, to secure adequate amount of and/or access to food (Barrett, 2010). Correspondingly, to weaken one's rivals, possessing and even destroying food sources is a beneficial strategy that increases the opponents' levels of food insecurity, negatively affecting their fighting ability (Hendrix and Brinkman, 2013).

For instance, to return to an example used previously, in Sierra Leone, troops of the Revolutionary United Front (RUF) burned and destroyed villages not only to secure food resources for their own consumption, but also to strategically hurt the government and prevent its troops from accessing these important resources (Keen, 2005). Similarly, in South Sudan, where "[e]thnic groups have fought each other over cattle—a vital part of the indigenous economy—for centuries" (Reuters, 2011), livestock raiding is frequently used to humiliate and weaken the enemy. Indeed, while analyzing every incidence of preemptive conflict over food security is beyond the scope of this chapter, a partial evaluation of more recent evidence—presented in Table 3.1—shows that preemptive conflict over food resources occurs relatively frequently. Distinguishing possessive conflict—i.e. conflict designed to increase one's own food security levels—from preemptive conflict—i.e., conflict designed to decrease one's rivals' food security levels—is complicated, as most conflict events over food resources is likely to involve elements of both. Hence, I only included in Table 3.1 cases where it was explicitly stated that the aim of using violence was to weaken or hurt other groups by appropriating or destroying locally produced food resources.

The raiders' strategy of expropriating and destroying the civilians' food resources to weaken their rivals during ongoing war combined with the civilians' strategy of providing their defense forces with varying levels of food support produce a "commitment problem" in my game model.[3] This commitment problem suggests that as long as the raiders cannot know in advance how much food support the civilians will provide to their defense forces, they might decide to attack and conquer areas with more food resources in order to control these focal points and cut the defense forces off from these resources. The value of the civilians' land is observable by all actors, which allows the raiders to estimate how much food is available in the region (e.g., in open stockpiles, granaries, and cattle pens). The importance of local food support to the defense forces' war efforts creates strong incentives for the raiders to *preemptively* target areas that offer *more* access to food resources, because doing so would weaken the defense forces, who require these resources to improve their own chances of victory. Preemptive conflict is

[3]Commitment problems arise when two actors know that they will prefer to renege on their agreement in the future, meaning that even a mutually beneficial agreement cannot be struck at present (e.g., Fearon, 1995). In the context discussed here, because the civilians decide their levels of food only after the raiders attack, neither side has a strong enough incentive to commit to finding a peaceful solution in advance.

Table 3.1: A Partial List of Preemptive Conflicts over Food Security

Country	Target	Raiders	Resource	Source
Angola	civilian farmers	rebels	crops	Macrae and Zwi (1992)
East Timor	civilians	rebels	livestock	The New Zealand Herald (2002)
El Salvador	civilians	gov. troops	crops	Messer and Cohen (2006)
Ethiopia (Tigre and Eritrea)	civilians, rebels	the *Derg*	crops, livestock	Keller (1992)
Ghana	herders	Farmers	crops, livestock	Tonah (2006)
India (Bastar)	CDF	Naxalite rebels	crops	Sundar (2007) PCI 2008
Italy (Sicily)	mafia	Mafia families	livestock	Blok (1969)
Kenya	ethnic militias	ethnic militias	livestock	Greiner (2013)
Mozambique	civilians, gov.	rebels	crops	Hultman (2009)
Nigeria (Biafra)	civilians	gov. troops	crops, stockpiles	Jacobs (1987)
Nigeria	herders	farmers	crops, livestock	Ofuoku (2009)
Peru (Tacuna and Arequipa)	CDF	rebels	crops, livestock	Masterson (1991) Walker (1999)
Sierra Leone	gov./CDF	rebels	crops	Mkandawire (2002) Keen (2005)
Somalia (Somaliland)	Civilians	political militias	crops, livestock	Ahmed and Green (1999)
Sudan (Darfur)	civilians, rebels	gov./militias	crops, livestock	de Waal (2005)
Sudan	ethnic Dinka	militias/gov.	livestock	Barrow (1996)
Sudan	S. Sudan	pastoralist militia	livestock	Leff (2009)
Thailand (Songkhla)	farmers, CDF	rebels	crops	The Nation (2004) Montesano and Jory (2008)
Uganda	civilians, LRA	military	crops, stockpiles	Doom and Vlassenroot (1999)
Vietnam	civilians, VC	military	crops	Leebaw (2014)

thus about *regulating the supply of food available to enemy groups.*[4]

The Model

Model Primitives

Assume three actors interacting in an agricultural region of a developing country: a set of civilians b (i.e. producers) who work the land to grow crops and livestock; raiders r (consisting of political or ethnic militias, rebels, etc.); and defense forces d (ethnic militias, civil defense forces, government troops, etc.). If attacked, the civilian producers decide the level of food support they provide to their defense forces $\theta \in [0,1]$, which is not revealed to the raiders until they invade the region. Thus, the civilians face a commitment problem; because they decide their level of food support only after being attacked, the raiders will always be concerned that areas with higher levels of food resources are going to improve the defense forces' chances of victory if the latter decide to open hostilities.[5]

Let ρ be the total probability that the defense forces defeat the raiders during war *taking the effect of food support into account*, such that $Pr(victory) \equiv \rho = p[1+(1-\delta)\theta\omega]$. In this probability function, $p \in [0,1]$ is the baseline probability of the defense forces' victory not accounting for the role played by local food support, i.e., based on the resources currently available to d. Additionally, let $\delta \in [0,1]$ denote the effect of violence on reducing θ, for example because targeting

[4]Note that this is not (necessarily) the same as "scorched earth" tactics, which involve the complete destruction of all means of production in a given area, whether the raiders conquer the region or not. As discussed here, "scorched earth" tactics are one extreme type of preemptive conflict, but they are neither the only one nor the most prevalent.

[5]In the model developed here, *how* food resources are provided and whether they are obtained using coercion or enticement is irrelevant. Because it revolves around a commitment problem, which relates to the sequential moves of different actors, the model is agnostic with respect to apportionment dynamics as highlighted by, e.g., Kalyvas (2006).

a food resource-abundant region enables the raiders to capture a high number of food stockpiles, kill civilians producers, or—in extreme cases—to employ "scorched earth" tactics. In this function, $\omega \leq \frac{1}{p} - 1$ denotes how important food support is to the defense forces' overall probability of victory. Both δ and ω guarantee that $p \in [0, 1]$. Setting ρ in this fashion thus incorporates the effect of local food support into local conflict patterns.

During war, the raiders r seek to target locations where food resources are grown and stockpiled to control these areas and prevent the defense forces d from gaining access to these resources. Let η be the costs the raiders incur from attacking a given region M, which includes the costs of mobilizing and recruiting individuals and obtaining firearms, such that $\eta > 0$. If r attacks and wins with probability $(1 - \rho)$ it obtains the benefit $R + s$, because controlling the region provides r with the access to both taxation and resource rents R, *and* the value of the land s, which includes the food produced and stockpiled by b.[6] If the raiders attack and lose, they receive no benefits, but still face the costs of attacking. If they do not attack, they simply maintain the status quo and gain a utility of zero. The raiders r's utility function from attacking the region (i.e., when $M = 1$, denoted simply as M for convenience) is thus: $U_r(M) = (1 - \rho) \times (R + s) + \rho \times 0 - \eta$, which can be rewritten as:

$$U_r(M) = (1 - \rho)(R + s) - \eta \tag{3.1}$$

Let θ be the amount of locally produced food the civilians b allocate to supporting their defense forces during war. Correspondingly, κ is the cost the civilians

[6] Because this chapter is focused on food support, the land's value s corresponds to its fertility and hence to the total amount of food that can be grown and stored on this land.

incur if the raiders attack the region where they live, e.g., through targeted or retributive killings. In addition, $c(\theta)$ is the opportunity costs of allocating food resources to support armed groups rather than keeping them for other uses, such that $c(\theta)\prime > 0$; $c(\theta)\prime\prime > 0$. For convenience, let $c(\theta) = \frac{1}{2}\theta^2$. Because ρ denotes the total probability with which the defense forces successfully protect the civilians and their land against the raiders, the civilians' benefit from victory is the total value of land (and the food produced and stored therein) in the region, which they get to keep, $\rho \times s$. If the raiders do not attack, the civilians keep the value of their land, s. If the raiders attack and the defense forces lose, then the civilians forfeit the entirety of their land, such that $(1 - \rho) \times 0$. The civilians' b utility function is thus expressed as:

$$U_b(M) = \rho s - \frac{1}{2}\theta^2 - \kappa \tag{3.2}$$

The civilian producers' optimization problem is to maximize Equation 3.2 with respect to θ, subject to the constraint $\theta \in [0, 1]$. Note that, in equilibrium, the civilians' action are assumed to reflect those of the defense forces; if they provide more food, the defense forces will be more likely to move into the region; if not, then the defenders will be less likely to do so. Thus, despite their importance, the defense forces are not a strategic actor in this model, and the variations in the outcome variable associated with the defense forces reflect right-hand side factors associated with the civilian producers in the strategic-statistical model discussed below. Nevertheless, for illustration purposes, the defense forces' utility function is still discussed here. To start, let ν be the cost the defense forces d incur from violent conflict in the region M, for example, due to the loss of lives or equipment, such that $\nu > 0$. In addition, if they defeat the raiders with probability ρ, the defense forces get to keep their rents R, e.g., through taxation, controlling natural resources production, etc., such that $\rho \times R$. If they lose, then they forfeit access to these rents, such that $(1-\rho) \times 0$. The defense forces' d utility function is thus:

$$U_d(M) = \rho R - \nu \tag{3.3}$$

.

The sequence of play is as follows. Nature draws the baseline probability of the defense forces' victory $p \in [0, \hat{p}]$, which is revealed to all actors. The raiders then need to decide whether or not to attack the region, $M \in \{0, 1\}$. Finally, the civilians determine the level of support they provide the defense forces, $\theta \in [0, 1]$. This order of play thus sets up the commitment problem.

Order of Play

Nature draws $p \in [0, \hat{p}]$

$M = 1$ $\qquad\qquad\qquad\qquad$ $M = 0$

$\theta \in (0, 1]$ $\qquad$ $\theta = 0$

Utilities

$\rho R - \nu$

$(1-\rho)(R+s) - \eta$ $\qquad\qquad\qquad$ $R,$ $0,$ s

$\rho s - c(\theta) - \kappa$ $\qquad$ $ps - \kappa$

- **Lemma 1:** *In the subgame perfect Nash equilibrium of the game between r, d, and b:*

(i) If attacked, the civilians b will always choose to provide some level of food support θ, considering its effect on improving the defense forces $d's$ overall probability of victory

(ii) The optimal agricultural food resources that the civilian producers b will allocate for the defense forces' consumption is $\theta^* = (1-\delta)\omega ps$

(iii) The utility of the raiders from (a) attacking the region, taking θ^* into account, is $U_r(M|\theta^*) = [1 - p(1 + (1-\delta)^2\omega^2 ps)](R+s) - \eta$, and consequentially (b) the raiders will attack if $U_r(M) = [1 - p(1 + (1-\delta)^2\omega^2 ps)](R+s) \geq \eta$

Proof: see appendix.

Lemma 1 establishes that in regions with some food resources, violent conflict might arise *endogenously*, as a consequence of the equilibrium choices between the civilian producers on the one hand, and the raiders on the other, during war. The intuition is straightforward in cases of linearly increasing food support θ: high enough levels of food support levels will guarantee the defense forces d's victory. However, as shown in Proposition 2 below, the stronger the effect of violence on reducing this support δ is, the more inclined the raiders will be to use it and initiate conflict. For instance, in South Sudan, some tribal militias routinely engage with the military and civil defense forces of ethnic groups associated with the regime over cattle theft, which frequently involves abuses against civilians (Reuters, 2011). These interactions are even more evident in Ethiopia, where large farms and food producers, which are defended by forces trained and managed by the state or by their own sponsored militias, experience frequent raids both by pastoralist groups—whose traditional space has been appropriated by these farms—and rebel groups who seek to challenge the state and its presence in the region (Mkutu, 2001).

The equilibrium results from Lemma 1 can be used to derive two sets of comparative statics to explain when the civilians will increase their level of food support, and when the raiders will prefer to target regions with more food resources. The first set of comparative statics is discussed in Proposition 1 below.

Proposition 1: *The level of food support θ^* provided by the civilians will, (i) increase in the case of stronger defense forces, which have a higher baseline probability of victory $p > 0$, (ii) increase when the marginal importance of food support to the defense forces d's strength is higher, and (iii) increase when the value of the food producing cropland in the region s is higher*

Proof: see appendix.

Proposition 1 serves as the basis for the ensuing comparative static prediction developed in Proposition 2, which explains *why* the raiders choose to target regions with more food resources. The rational behind Proposition 1 is intuitive. Recall that more access to food resources provided by the local civilians increases the ability of troops to operate for longer periods of time and attract more recruits. Additionally, θ is a finite resource because the civilian producers b cannot provide more food than they can physically produce and stockpile due to limitations in infrastructure that force communities and individuals across the developing world to rely on food produced locally (Paarlberg, 2000; Henk and Rupiya, 2001).

Importantly, military and civil defense forces across the developing world are also frequently forced to rely on food produced and grown locally during war, due to the relative lack of guaranteed logistic support provided by the state (Koren and Bagozzi, 2016, 2017). If the defense forces are strong and have a high probability of victory as captured by the *exogenous* parameter p, providing food support is more likely to "pay off" because the civilians will be able not only to keep their remaining resources for consumption, but also avoid potential retribution. Correspondingly, if local food support is important to ensuring the defense forces' victory (as captured by the ω parameter), it follows that the civilian producers will allocate support simply because, bushel to bushel, and all else equal, they gain higher marginal returns with respect to improving the defense forces' chances of victory for the same amount of food.

The model's finding that the civilians will provide higher levels of food support when the land is more valuable is also intuitive. Valuable land is more fertile, and allows for more food to be produced. This in turn means that the civilians not only have a higher incentive to defend this valuable land, but also that they can provide more food support and gain a higher marginal utility from investing in defending these resources.

As a result, in equilibrium, the raiders will realize that the civilians residing in regions with more arable land will always allocate some of these resources to support the defense forces, and that hence higher levels of food support θ are a credible threat. Higher allocations of θ decrease the raiders' overall probability of victory, and it is this intuition that explains *why* the raiders would choose to attack areas with more food crops. This intuition is formalized in Proposition 2 below.

Proposition 2: *the higher the effect of attacking on reducing the level of civilian food support δ is, (i) the utility of the raiders r from attacking will increase;*

and (ii) the level of the defense forces' strength above which the raiders will chose to attack (captured by baseline probability of defender victory) $\bar{p}$ *will increase*

Proof: see appendix.

Targeting regions with more food resources allows the raiders to *preemptively* weaken the defense forces by limiting their supply of available food during war. This becomes an especially attractive strategy for the raiders if violence has a strong effect on reducing this support. Indeed, Proposition 2 explains why the raiders' strategic calculations are likely to be affected by food resource-related concerns, and hence why preemptive violence over food resources might be more prevalent, perhaps, than initially expected. The first part of this proposition establishes that preemptively targeting regions with more food resources is an effective strategy to increase the raiders' chances of victory. The second part of Proposition 2, however, shows that—if the use of violence to reduce food support is highly effective—the raiders might attack even regions where the defense forces are relatively strong, which would otherwise serve to deter potential raiders from attacking. Thus, the more effective preemptive conflict is in reducing food support during war, the more prevalent it will be.

This does not necessarily mean that targeting regions where violence has a strong effect on reducing food support will involve a high number of *combatant* casualties. Some wars involve a relatively low number of armed combatants' deaths, yet a high number of civilian casualties (Valentino, Huth and Balch-Lindsay, 2004). The raiders might prefer to use atrocities to directly hurt the defense forces' channels of food support in cases when the latter are too strong to be defeated militarily (Wood, 2010). Atrocities can also be used as a strategy designed to subdue or influence the local population to keep θ at low or zero levels (Kalyvas, 2006), especially in cases where conflict occurs between different ethnic groups (Fjelde and Hultman, 2014). In both cases, preemptive violence results from the fact that the raiders must choose the timing and the location for the attack before the civilians decide on the levels of food support θ they provide. I thus consider civilian victimization alongside other forms of more traditional armed conflict, both in the theoretical model and in the empirical section.

Proposition 2 suggests that higher levels of food support θ will be associated with a higher likelihood of violent conflict, which in turn builds on the logic that civilians will habitually provide some level of food support to the defense forces if the raiders attack. Note that the exact levels of θ that the civilians b might eventually provide to the defense forces d cannot be observed *ex ante* by the raiders r. The raiders, however, can observe the value of the land s and extrapolate from this value whether the civilians will provide θ, and whether food support levels are likely to be high.

The preemptive conflict framework therefore provides one explanation for why within the state conflict tends to concentrate in areas with an abundance of food resources and not where food is scarce. Rather than thinking of conflict over food resources as a pressure on consumption, which is the focus of numerous studies of the food-conflict nexus (Burke et al., 2009; O'Loughlin et al., 2012; Bagozzi, Koren and Mukherjee, 2017), it might therefore also be useful to theorize it as a weapon. Under this framework, actors seek to possess food resources not for consumption to improve their own dietary energy availability or to reward supporters, but rather to worsen their opponents' fighting capabilities by denying them access to food. Food denial has been used repeatedly to weaken and defeat one's opponents throughout history, with some notable instances including the Allied blockade of Germany during World War I (Downes, 2008), the Soviet *Holodomor* famine in Ukraine (Snyder, 2010), and the Ethiopian Derg regime's intentional starvations of Tigre and Eritrea (Keller, 1992). These instance, which show that planned famines can be used as a *macro* level strategy to destroy one's opposition, complement my model and the campaigns documented in Table 3.1 above, which show that the destruction of food producing lands can also be initiated as *micro* level tactics to achieve the same aim at the subnational level.

Building on Propositions 1 and 2, my model suggests that the civilians b are likely to provide at least some food support to d to increase the latter's overall probability of victory, which prompts the raiders r to preemptively target these regions in order to weaken the defense forces. The raiders cannot know *ex ante* if the civilians will provide food support to the defense forces, or—if they do decide to allocate support—how much food will they provide. However, because the raiders can observe s, i.e., the value and fertility of the land in the region, they are more likely to target areas where there are some food resources, and especially regions where food is abundant, assuming that in these regions more food is likely to be available to support the defense forces, and hence that (a higher level of) food support is more likely. They might be especially likely to attack these areas if violence has a strong effect on reducing food support levels. This accordingly suggests the following expectation:

- **E1:** The raiders' utility from attacks increases in regions where more food crops are grown

Moreover, the higher the baseline probability of the defense forces' victory, the greater the marginal benefits the civilians gain from providing food support. Higher levels of food support thus increases the probability that the defense forces will be willing or able to respond to attacks by raiders. This suggests the following expectation:

- **E2:** The defense forces will be more likely to respond to raider attacks in areas with more available food for consumption

Empirical Analysis

The equilibrium and comparative static results derived above are statistically evaluated on a subnational sample of countries for the years 1998-2008. Moreover, to verify that any identified effects are also substantively sizable (Greenhill, Ward and Sacks, 2011), I use the resulting estimates to forecast conflict on a second sample for the years 2009-2010 and show that local food production is also a significant *predictive* indicator of localized conflict. Doing so will add both to research concerned with the strategic behaviors of different groups during conflict, as well as inform the work of policymakers concerned with identifying and preventing violence.

The tree game presented above can be expressed in statistical terms. This statistical strategic model ensures that the interactive nature of preemptive conflict over food resources is adequately captured and—importantly—that the model is correctly identified in respect to these dynamis (Signorino and Yilmaz, 2003; Carter, 2010). The strategic logit equivalent of this game necessitates making the plausible assumption that all actors operate rationally within limitations (i.e. bounded rationality), and that they hence play with some error (Signorino, 1999; Signorino and Yilmaz, 2003). This allows me to implement the logit quantal response equilibrium solution concept (LQRE) to analyze the strategic dynamics in this game (Signorino, 1999; Carter, 2010). A special case of the LQRE in which there is no uncertainty is used to solve the theoretical model. This empirical model is thus structurally consistent with the theoretical model but also accommodates errors to be made by the different actors. This statistical model captures the idea that the raiders and civilians each make decisions in the game by weighing their expected utilities for each possible action. In this case, it is useful to begin with the last step in the game, the decision of the civilians to provide food support or not, and then move up the tree following each player's calculations. For each observation, $i = \{1, 2, 3...n\}$, the civilians need to decide the level of food support they provide if they observe the raiders invading. If the raiders preemptively attack, i.e., if $M = 1$, then—as illustrated in the proof of Lemma 1—the civilians make the following comparison:[7]

$$
\begin{aligned}
p_{b,i|F} &= U_b^*(F|A) \geq U_b^*(\neg F|A) \\
&= U_b(F|A) + \epsilon_F \geq U_b(\neg F|A) + \epsilon_{\neg F}
\end{aligned}
\tag{3.4}
$$

Assuming the error terms are independent and identically distributed (i.i.d.) Type 1 Extreme Value yields:

$$
\begin{aligned}
p_{b,i|F} &= \frac{exp^{U_b(F|A)}}{exp^{U_b(F|A)} + exp^{U_b(\neg F|A)}} \\
p_{b,i|\neg F} &= 1 - p_{b,i|F}
\end{aligned}
\tag{3.5}
$$

[7]Note that F stands for feed and A for attack.

The raiders make their decision to attack or not by comparing, with some error, their utility from the status quo, $U_r(SQ)$, i.e., the utility they gain from not initiating conflict, to their utility from attacking, which is calculated by multiplying each of the two possible outcomes with the probability that each is realized. Assuming, again, that the error terms are i.i.d. Type 1 Extreme Value:

$$p_{r,i|A} = \frac{exp^{(p_{b,i|F})U_r(A,F)+(p_{b,i|\neg F})U_r(A,\neg F)}}{exp^{(p_{b,i|F})U_r(A,F)+(p_{b,i|\neg F})U_r(A,\neg F)} + exp^{(p_{r,i|\neg A})U_r(SQ)}} \tag{3.6}$$

Model Specification and The Dependent Variable

To specify the statistical version of the game with regressors, identification issues must satisfy theoretical expectations. The utility of at least one possible outcome at the initial information set for both civilians and raiders, which can thus influence their utilities, is normalized to zero (Signorino, 1999). As no regressor can be included in every utility estimation, all coefficients are evaluated with respect to an outcome where the raiders attack, but the civilians decide *not to provide food support*, which is correspondingly normalized to zero (see, Signorino and Yilmaz, 2003). So, for example, a positive coefficient on, say, food crops means that attacking more fertile land increases the raiders' utility when the civilians decide to provide food support compared with a situation when they decide not to do so.

The model derived above is tested on subnational data for all countries in Africa encompassing 11 years (1998-2008) for which information on all variables was available. Africa was chosen as the focus of empirical analysis for three reasons. Firstly, the Armed Conflict and Location and Event Data (ACLED) Version 6 dataset (Raleigh et al., 2010), which provides one of the most exceptional coverages of a wide variety of violence types at the highly localized level (an which was used for analyses conducted in Chapter 1), covers almost exclusively African countries. Moreover, the ACLED dataset includes a broad spectrum of dyadic interactions that go beyond the traditional government vs. rebel logic, which allows my statistical model to capture manifestations of violence that are more likely to characterize localized conflict, such as the killing of civilians or inter-communal attacks. Secondly, the focus on Africa as the world region currently most susceptible to the effects of food insecurity—through climatic variability or otherwise—corresponds to previous studies on climatic variation, food security, and conflict, which similarly focus on the same region (Burke et al., 2009; Buhaug, 2010; O'Loughlin et al., 2012). Finally, considering the size of the dataset and the necessity to rely on computer simulations for deriving statistical estimation, any larger sample would have presented significant—and insurmountable, based on available resources—computational challenges.

The dependent variable must capture the decisions made at each node, by the raiders on the one hand, and the civilians on the other, which—in respect to food support—is reflected by the actions of the defense forces. The ACLED dataset draws on (i) information from local, regional, national and continental media reviewed daily; (ii) NGO reports used to supplement media reporting in hard to access cases; and (iii) Africa-focused news reports and analyses integrated to supplement daily media reporting. Building on the formal model, the defense forces' actions reflect the civilians' decision to allocate varying levels of food support. The defense forces can thus either defend the civilians against raids (play D) or not (play $\neg D$). The defense forces—defined as state forces, or as pro-government or ethnic militias—are coded as playing Defend if they are involved in any type of *violent* conflict[8] against the raiders—where the raiders are coded as the *initiating* actor—in a given cell during a given year, not Defend otherwise. Correspondingly, there are two discrete actions for the raiders: to attack (play A) or not attack (play $\neg A$).[9] The raiders are defined as having played Attack if they are recorded to *initiate* a conflict (including one sided attacks against civilians) in a given cell during a given year, whether it was responded to by a group identified as defense forces or not, not Attack otherwise. For summary purposes, the frequencies of raider attacks and defender responses for the years 1998-2008 are reported in the Figure 3.1 below.

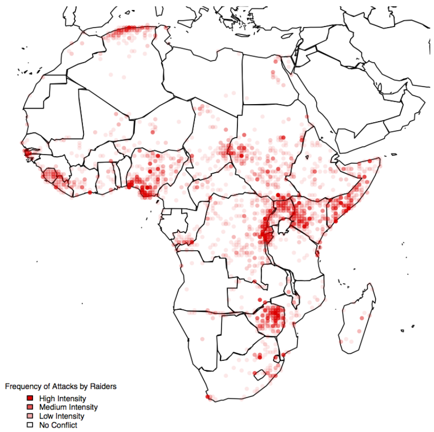
The violent conflict data from the ACLED Version 6 dataset and all other indicators are structured into a cell-year level dataset wherein cells—my cross-sectional unit of interest—are measured at the 0.5 x 0.5 decimal degree resolution[10] for all African land areas annually (t) (Tollefsen et al., 2012). There are approximately 10,674 cells observed for any given year within the 1998-2008 sample period, with the average country containing roughly 201 cells. For summary purposes, the distribution of raider attacks and defense forces responses are plotted by grid cell for the entire period and annually in Figure 3.2 below.

[8]I.e., events *not* coded by the ACLED Version 6 dataset as: "Headquarters or base established" or "Non-violent activity by a conflict actor" or "Riots/Protests" or "Non-violent transfer of territory" or "Strategic development" (Raleigh and Dowd, 2015).

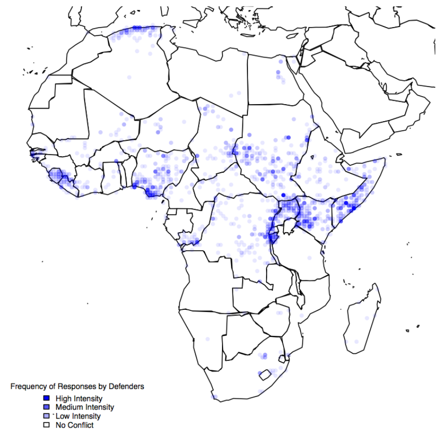
[9]In line with theoretical expectations, the raiders were defined as actors "who seek the replacement of the central government, or the establishment of a new state" or as " armed agents supported by political elites of various types, seeking to influence political processes but not change the government" or as "groups engaged in local political competition, often traditionally based contests between ethnic, community or local religious groups" (Raleigh and Dowd, 2015, 16-17).

[10]I.e., cells of approximately 55 x 55 kilometers at the equator (3025 square kilometer area).

Figure 3.1: The Regional Distribution of Attacks by Raiders and Responses by Defense Forces, 1998-2008

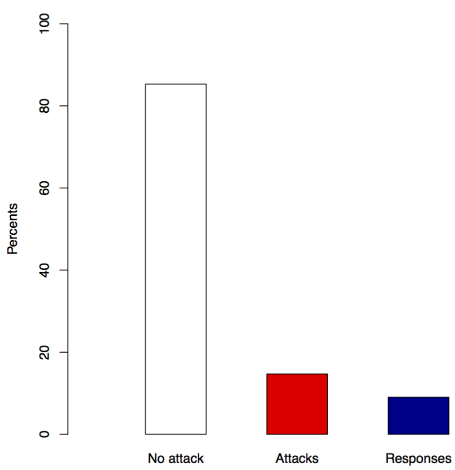


Raider Attacks, 1998-2008

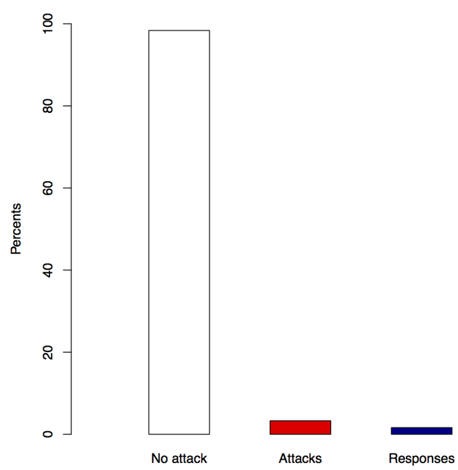


Defender Responses, 1998-2008

Figure 3.2: The Distribution of Raider Attacks and Defense Forces Response by Grid Cell and Cell-Year, 1998-2008



Distribution by Grid Cell



Distribution by Grid Cell Year

Regressors

The specification of the raiders' utility for the status quo must include the key variables that influence their decision to initiate preemptive conflict over food security. First, potential attackers are likely to employ violence in response to previous provocations, or in locations where they have attacked previously (e.g., Buhaug, Gates and Lujala, 2009). Second, lagged indicators of development and political openness have been shown to be consistent predictors of conflict (Fearon and Laitin, 2003). Therefore, to model the raiders' utility from the status quo, historical context indicators impacting the raiders' propensity to initiate conflict are included in this equation. These indicators include: the number of all political violence-related events by all types of actors, state and nonstate, that occurred in a given cell the previous year (Raleigh et al., 2010); the gross domestic product (GDP) per capita for the previous year (World Bank, 2012); and the level of political openness in the previous year as measured by the Polity2 indicator (Marshall, Jaggers and Gurr, 2013). Cubic, binary, and linear time polynomials are then added to capture the effect of time trends more broadly (Carter and Signorino, 2010). The expectations is that the raiders will be more likely to attack in territories previously lost and following battlefield loses, as well as in countries with lower levels of state capacity and more politically restrictive regimes. The raiders' utility from the status quo is thus modeled as:

$$\begin{aligned} U_r(SQ) = \beta_{SQ,0} + \beta_{SQ,1} Conflict_{t-1} + \beta_{SQ,2} GDPPerCapita_{t-1} + \\ \beta_{SQ,3} Polity2_{t-1} + \beta_{SQ,4} Time + \beta_{SQ,5} Time^2 + \beta_{SQ,6} Time^3 + \alpha_{SQ} \end{aligned} \tag{3.7}$$

To measure s—i.e. the value of land that is observed by all actors—in the *raiders*' utility function, I employ a highly localized food access indicator, *Cropland*, created by Ramankutty et al. (2008). This indicator measures the total area of a pixel—i.e., a cell the size of 0.08 x 0.08 degrees—covered by any type of staple cropland, which was then aggregated to the 0.5 x 0.5 degree level. This variable was created in a manner similar to that of the maize and yield indicators discussed in Chapter 2, although it is constant for the year 2000, due to data availability.

Approximating the actual levels of food support provided by the civilians is more complicated, as such an indicator should, at the very least, closely approximate the actual amounts of food that could be *consumed or stored* in a given region during a given year. This means that more perishable resources such as vegetables are less than ideal for this purpose, and that an adequate indicator of θ should—at the very least—be based on a more durable food crop. Moreover, the value of θ is, to some extent, dependent on s, so an effective parametrization should capture this relationship, again considering that no one regressor can be present in all utility functions (Signorino and Yilmaz, 2003).

Therefore, to approximate θ I rely on an indicator measuring the annual yields of wheat by grid cell (Ray et al., 2012). Wheat was chosen because as a staple food for about 35% of the world's population, it provides more calories and protein in the world's diet than any other crop, and can be stored for relatively long periods of time (Food and Agricultural Organization of the United Nations, 2016). Moreover, in Africa—and especially sub-Saharan Africa—wheat is in exceptionally high demand, which cannot be met by production supply (Asfaw Negassa et al., 2013), making this crop an especially valuable food resource to measure the responsiveness of different defense forces. The focus on yields, specifically, approximates better the amounts of food that are immediately available (e.g., in stockpiles) for consumption. This indicator—the same as the wheat indicator used in Chapter 2—thus provides an exceptional coverage of the annual variation in food availability at the highly localized level ($\sim$0.08° grids, averaged to the 0.5° grid level), which is a major improvement over past studies of this sort that have favored static measures of cropland at comparable levels of geographic resolution (e.g., Koren and Bagozzi, 2016; O'Loughlin et al., 2012).

Several additional variables (some of which are not explicitly discussed above) that might influence parameters in the theoretical model are also included in the utilities of both actors from conflict. These indicators are all measured at the *cell* rather than country level, which adequately accounts for the effects of these variables at the highly localized level. First, an indicator denoting gross cell product in a given year (measured in billion USD), *GCP* (Nordhaus, 2006), is included to account for the potential effect of valuable rents R, which—as the formal model shows—might provide added incentives for violence. Second, the number of people in a given cell, *Population* (Nordhaus, 2006), is included to account for the potential effect of population density on the raiders' propensity to employ violence. Thirdly, because attacks might be more likely in grid cells that were recently conquered by rival groups (Raleigh et al., 2010), an indicator denoting whether territorial change has occurred, *Terr. Change*, is also included. Fourth, considering that conflict might be more likely in rural areas or regions closer to the border (Buhaug, Gates and Lujala, 2009), indicators measuring the distance from each cell to the nearest city with more than 50,000 inhabitants (*Travel Time*) and to the nearest border (*Border Distance*) are also added. Fifth, indicators measuring average annual temperature (*Temperature*) and rainfall (*Precipitation*) levels are included to control for the effect of these factors on food production and correspondingly on conflict; and because these indicators are used by many studies on the climate-conflict nexus (e.g., Burke et al., 2009; O'Loughlin et al., 2012; Miguel, Satyanath and Sergenti, 2004). Finally, similarly to Equation 3.7, time polynomials are included to account for time trends in both equations. Thus, the utilities for conflict outcomes are:[11]

$$\begin{aligned} U_r(AF) = {} & \beta_{r|AF,0} + \beta_{r|AF,1} Cropland + \beta_{r|AF,2} Population + \\ & \beta_{r|AF,3} GCP + \beta_{r|AF,4} TerritorialChange + \beta_{r|AF,5} TravelTime + \\ & \beta_{r|AF,6} BorderDistance + \beta_{r|AF,7} Temperature + \beta_{r|AF,8} Precipitation + \\ & \beta_{r|AF,9} Time + \beta_{r|AF,10} Time^2 + \beta_{r|AF,11} Time^3 + \alpha_{r|AF} \end{aligned} \tag{3.8}$$

$$\begin{aligned} U_b(AF) = {} & \beta_{b|AF,0} + \beta_{b|AF,1} WheatYield + \beta_{b|AF,2} Population + \\ & \beta_{b|AF,3} GCP + \beta_{b|AF,4} TerritorialChange + \beta_{b|AF,5} TravelTime + \\ & \beta_{b|AF,6} BorderDistance + \beta_{b|AF,7} Temperature + \beta_{b|AF,8} Precipitation + \\ & \beta_{b|AF,9} Time + \beta_{b|AF,10} Time^2 + \beta_{b|AF,11} Time^3 + \alpha_{b|AF} \end{aligned} \tag{3.9}$$

Summary statistics for all variables are reported in Table 3.2 below.

[11] Because including lagged measures without theoretical justifications can introduce inferential biases (Bellemare, Masaki and Pepinsky, Forthcoming), these variables were not lagged. My findings are robust to this decision, as demonstrated in Table 3.7 below.

Table 3.2: Summary Statistics of All Variables Used in Chapter 3 (1998-2008)

	Minimum	Median	Mean	Max	SD
Raider Attacks	0	0	0.033	1	0.179
Defender Responses	0	0	0.016	1	0.127
Cropland	0	0.021	0.085	1	0.154
Wheat Yield	0	2.63E-5	0.009	0.930	0.047
Population[1]	0	9.721	9.369	16.268	2.263
GCP_t[1]	0	0.076	0.270	4.455	0.490
Terr. Change	0	0	0.007	1	0.081
Travel Time[1]	0	6.127	6.187	8.722	0.855
Border Distance[1]	0	4.913	4.682	7.574	1.137
Temperature	3.625	24.675	24.382	32.617	3.774
Precipitation[1]	4.220	6.155	5.981	8.417	1.016
Conflict_{t-1}	0	0	0.316	506	3.890
GDP Per Capita_{t-1}[1]	5.338	7.317	7.523	10.268	1.094
Polity2_{t-1}	-9	-1	-0.025	10	5.129
Urban	0	0	0.099	51.549	0.901
Capital Distance[1]	1.609	6.319	6.228	7.818	0.795
Mountains	0	0	0.123	1	0.243
Military Expenditure_{t-1}[1]	0	12.612	12.525	15.350	1.649
Attack Spl. Lag	0	0	0.060	1	0.237

[1] Natural log

Results

Main Findings

The regression estimates in Table 3.3 provide strong support for the expectations derived from the theoretical model. One issue with standard errors in strategic statistical models is that the use of a choice-based sample might introduce bias, while the assumption of independence across within-group observations is violated (Carter, 2010). To account for these potential heterogeneities and other issues, I use bootstrapping undertaken based on 1,000 draws, with sampling clustered by each player. Specifically, the standard errors are clustered for each regression stage by the player whose utilities are captured in this stage. This takes into account the plausible possibility that errors are heterogeneous between different grid-cells and years for the same players.

In line with E1, the likelihood of raider attacks significantly increases in areas

Table 3.3: Player Utilities for Raids and Defenses, 1998-2008

	$U_r(AF)$	$U_b(AF)$	$U_r(SQ)$
Cropland	1.661*	–	–
	(0.342)		
Wheat Yield	–	0.173*	–
		(0.072)	
Population[1]	-2.193*	-0.096*	–
	(0.599)	(0.016)	
GCP[1]	-6.862*	-0.152*	–
	(1.485)	(0.025)	
Terr. Change	25.486*	0.576*	–
	(3.111)	(0.202)	
Travel Time[1]	-2.538*	-0.056*	–
	(0.879)	(0.022)	
Border Distance[1]	-1.114*	-0.019*	–
	(0.360)	(0.008)	
Temperature	0.551*	0.014*	–
	(0.118)	(0.004)	
Precipitation[1]	-4.345*	-0.122*	–
	(1.080)	(0.021)	
Conflict_{t-1}	–	–	-0.145*
			(0.022)
$\text{GDP Per Capita}_{t-1}$[1]	–	–	0.116*
			(0.056)
Polity2_{t-1}	–	–	0.067*
			(0.008)
t	6.006	-0.106	6.617
	(5.071)	(0.096)	(5.124)
t^2	0.225	-0.007	0.124
	(0.692)	(0.017)	(0.676)
t^3	-0.043	-0.001	-0.039
	(0.034)	(0.001)	(0.032)
Constant	-90.452*	2.817*	-93.224*
	(28.427)	(0.325)	(26.247)

Number of observations: 63,218

Akaike Information Criterion: 20,831.61

* indicates $p < 0.05$.

Values in parentheses are standard errors clustered by player and bootstrapped using 1000 iterations.

$U_b(A\neg F)$ is the reference node and was normalized to zero.

[1] Natural log

with more staple cropland. Because the raiders cannot know the levels of food support the defense forces will receive in advance (if any), attacking areas with more cropland is a significantly preferred strategy according to the model. These results hold even with the inclusion of relevant controls. The coefficients of *Terr. Change* and *Temperature* are positive and significant while the coefficients of *Population*, *Travel Time*, *Border Distance*, *GCP*, and *Precipitation* are negative and significant, suggesting that these factors also have an observable effect on the utilities of the raiders from initiating localized conflict. The coefficients in the raiders' utility from the status quo also follow theoretical expectations. The raiders will gain from the status quo in locations and years where there is little history of conflict, which lessens the pressures on groups to initiate preemptive conflict to weaken their rivals as a defensive strategy; in countries with higher average income, where it is not necessary for food to be grown locally because it can be easily obtained via alternative means (e.g., refrigeration, improved transportation due to better infrastructure); and in countries with more political participation, which allows different groups to resolve potential conflicts in peaceful ways.

In line with E2, the probability of defense forces responding to attacks significantly increases in areas and years with higher values of *Wheat Yield*. Higher yields correspond to higher levels of food support (as shown in the formal model), which allow the defense forces to operate freely and for longer periods of time, and attract more recruits if needed. By capturing the civilians' incentives to provide food (as derived in Proposition 1) in addition to the levels of food available in a given grid cell during a given year, this indicator provides a close approximation of θ levels. This suggests that providing higher levels of food support is a significantly preferred strategy by the civilians according to the model. Again, these results hold even with the inclusion of climatic variables. The coefficients of *Precipitation*, *Population*, and *GCP*, *Travel Time*, and *Border Distance* are negative and significant, while *Terr. change* and *Temperature* are positive and significant.

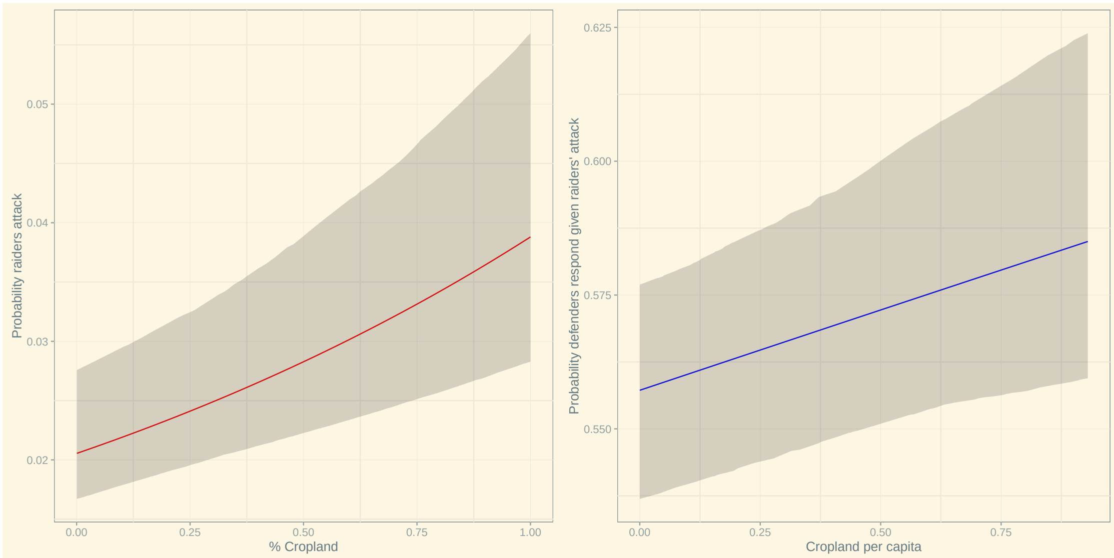
To verify whether these strategic interactions also have a substantive effect on the probability of raids and defense forces' responses, I also evaluate how the level of cropland and wheat yields increases the predicted probabilities of these phenomena. The predicted change in the probability of raids in based on staple cropland availability, and the predicted change in the probability of defenders responding to attacks based on wheat yield values are presented in Figure 3.3, with bootstrapped 95% confidence intervals, while holding all other variables to their medians or means. As illustrated by these plots, the utility of raiders from attacking a given region increases by 2.5% on average across the range of *Cropland*. Similarly, the utility of the civilians increases by about 2% across the entire range of *Wheat Yield*, as this suggests that higher levels of food support mean that the defenders are more likely to respond. These quantities are relatively quite sizable considering the relative rarity of conflict in my sample, and suggest a substantive impact of locally grown resources on localized conflict.[12]

Robustness Analyses

To verify the robustness of these findings to alternative mechanisms, in this section I reestimate this model using six different specifications. First, the effect of urbanization on the utilities of the raiders and the civilians is more throughly taken

[12]From a comparative example, the coefficient for *GCP* have almost no effect on the decision of the raiders to attack a given location.

Figure 3.3: Predicted Probabilities From Preemptive Conflict



Effect of Cropland on Raids | Effect of Wheat Yields on Defenses

into account by including an indicator measuring the level of urbanization in each grid cell in the equations capture the raiders' and defense forces' utilities in Table 3.4. Second, numerous studies have equated a higher likelihood of conflict with lower state capacity levels (e.g., Fearon and Laitin, 2003). To account for this possibility, Table 3.5 estimates the primary model with the inclusion of distance to capital and the percentage of a given cell that is mountainous, in a manner used in past studies (Fearon and Laitin, 2003; Fjelde and Hultman, 2014). Third, attacks in certain grid cells might be caused because attacks nearby push raiders to attack these cells due to their vicinity, i.e., conflict can simply spill over from a neighboring cell. To account for this possibility, Table 3.6 includes spatial lags of raider attacks in the raiders' utility function.

Fourth, recall that none of the independent variables (excluding the lag of the dependent variable) were lagged due to the potential misspecification issues and inferential biases that might result (Bellemare, Masaki and Pepinsky, Forthcoming). Nevertheless, to show that my results are robust to this decision, a model where all time varying indicators are lagged by one year is reported in Table 3.7. Fifth, the size of a given state's military might influence the raiders' decision whether to initiate conflict or pursue more peaceful solutions under the status quo. To account for this possibility, a model that includes lagged military expenditure in the raiders' utility from the status quo (obtained from the Correlated of War dataset Singer, Bremer and Stucky, 1972) is reported in Table 3.8 to account for the potential effects of military (i.e., defense force) size on the raiders' decision to attack. Finally, to show that the results are not driven by my choice of controls or the number of indicators included in the model, a baseline specification of the primary analysis using only a small number of variables in the utility functions of the both the raiders and the civilians. Crucially, the significance and sign of *cropland* and *wheat yields* is consistent across these different specifications, which additionally confirms the argument developed in the previous section.

Table 3.4: Player Utilities for Raids and Defenses, 1998-2008, With Urbanization

	$U_r(AF)$	$U_b(AF)$	$U_r(SQ)$
Cropland	1.802*	–	–
	(0.331)		
Wheat Yield	–	0.318*	–
		(0.072)	
Population[1]	-1.224*	-0.134*	–
	(0.558)	(0.015)	
GCP[1]	-7.051*	-0.256*	–
	(1.644)	(0.027)	
Terr. Change	19.633*	0.808*	–
	(2.934)	(0.195)	
Travel Time[1]	-1.636	-0.062*	–
	(0.845)	(0.023)	
Border Distance[1]	-0.863*	-0.025*	–
	(0.328)	(0.008)	
Temperature	0.416*	0.020*	–
	(0.128)	(0.003)	
Precipitation[1]	-3.010*	-0.162*	–
	(1.003)	(0.020)	
Urbanization	1.023*	0.033*	–
	(0.359)	(0.006)	
Conflict$_{t-1}$	–	–	-0.143*
			(0.022)
GDP per capita$_{t-1}$[1]	–	–	0.081
			(0.057)
Polity2$_{t-1}$	–	–	0.066*
			(0.008)
t	-2.195	0.096	-2.230
	(8.132)	(0.153)	(8.088)
t^2	1.064	-0.043	1.088
	(1.097)	(0.023)	(1.077)
t^3	-0.073	0.003*	-0.075
	(0.050)	(0.001)	(0.048)
Constant	-35.796	3.157*	-39.785
	(34.374)	(0.378)	(30.389)

Number of observations: 63,218
Akaike Information Criterion: 20,796.49
* indicates $p < 0.05$.
Values in parentheses are standard errors clustered by player and bootstrapped using 1000 iterations.
$U_b(A\neg F)$ is the reference node and was normalized to zero.
[1] Natural log

Table 3.5: Player Utilities for Raids and Defenses, 1998-2008, With State Capacity Indicators

	$U_r(AF)$	$U_b(AF)$	$U_r(SQ)$
Cropland	1.563*	–	–
	(0.377)		
Wheat Yield	–	0.168*	–
		(0.072)	
Population[1]	-2.107*	-0.098*	–
	(0.904)	(0.018)	
GCP[1]	-1.858	-0.058	–
	(3.022)	(0.067)	
Terr. Change	24.296*	0.583*	–
	(3.329)	(0.284)	
Travel Time[1]	-1.624	-0.033	–
	(1.229)	(0.034)	
Border Distance[1]	-0.862	-0.016	–
	(0.498)	(0.013)	
Temperature	0.950*	0.021*	–
	(0.170)	(0.008)	
Precipitation[1]	-3.465	-0.111*	–
	(1.896)	(0.045)	
Mountains	2.379	-0.010	–
	(1.282)	(0.036)	
Capital Distance[1]	3.592*	0.077*	–
	(1.037)	(0.037)	
Conflict$_{t-1}$	–	–	-0.146*
			(0.023)
GDP per capita$_{t-1}$[1]	–	–	0.099
			(0.056)
Polity2$_{t-1}$	–	–	0.050*
			(0.008)
t	3.806	0.080	4.237
	(5.098)	(0.100)	(5.085)
t^2	0.443	-0.009	0.337
	(0.704)	(0.017)	(0.672)
t^3	-0.051	0.001	-0.045
	(0.034)	(0.001)	(0.031)
Constant	-121.80*	1.830*	-80.356
	(32.164)	(0.904)	(27.183)

Number of observations: 62,567
Akaike Information Criterion: 20,419.50
* indicates $p < 0.05$.
Values in parentheses are standard errors clustered by player and bootstrapped using 1000 iterations.
$U_b(A\neg F)$ is the reference node and was normalized to zero.
[1] Natural log

Table 3.6: Player Utilities for Raids and Defenses, 1998-2008, With Spatial Lag Attacks

	$U_r(AF)$	$U_b(AF)$	$U_r(SQ)$
Cropland	1.330*	–	–
	(0.380)		
Wheat yield	–	0.259*	–
		(0.100)	
Population[1]	-1.186*	-0.113*	–
	(0.403)	(0.022)	
GCP[1]	-3.548*	-0.151*	–
	(1.340)	(0.037)	
Terr. Change	21.832*	1.095*	–
	(5.430)	(0.259)	
Travel Time[1]	-1.026	-0.042	–
	(0.890)	(0.032)	
Border Distance[1]	-0.376	-0.005	–
	(0.332)	(0.014)	
Temperature	0.406*	0.019*	–
	(0.111)	(0.005)	
Precipitation[1]	-2.109*	-0.108*	–
	(0.948)	(0.041)	
Attack Spl. Lag	5.867*	–	–
	(0.189)		
Conflict_{t-1}	–	–	-0.065*
			(0.012)
$\text{GDP Per Capita}_{t-1}$[1]	–	–	0.087
			(0.061)
Polity2_{t-1}	–	–	0.049*
			(0.009)
t	-11.822	0.360	-10.821
	(9.140)	(0.277)	(8.759)
t^2	2.209	-0.071	2.065
	(1.439)	(0.046)	(1.366)
t^3	-0.113	0.004	-0.107
	(0.070)	(0.002)	(0.066)
Constant	-26.354	1.691*	-18.649
	(25.927)	(0.662)	(20.321)

Number of observations: 63,163
Akaike Information Criterion: 19,119.33
* indicates $p < 0.05$.
Values in parentheses are standard errors clustered by player and bootstrapped using 1000 iterations.
$U_b(A\neg F)$ is the reference node and was normalized to zero.
[1] Natural log

Table 3.7: Player Utilities for Raids and Defenses, 1998-2008, With Lagged Independent Variables

	$U_r(AF)$	$U_b(AF)$	$U_r(SQ)$
Cropland	1.455*	–	–
	(0.322)		
Wheat Yield$_{t-1}$	–	0.113*	–
		(0.034)	
Population$_{t-1}$[1]	4.270*	0.051*	–
	(0.788)	(0.008)	
GCP$_{t-1}$[1]	7.198*	0.158*	–
	(1.655)	(0.022)	
Terr. Change$_{t-1}$	-9.589	-0.224*	–
	(5.647)	(0.056)	
Travel Time[1]	1.413	0.036*	–
	(1.185)	(0.016)	
Border Distance[1]	1.219*	0.029*	–
	(0.540)	(0.007)	
Temperature$_{t-1}$	-5.700*	-0.010*	–
	(0.179)	(0.002)	
Precipitation$_{t-1}$[1]	7.842*	0.132*	–
	(1.298)	(0.017)	
Conflict$_{t-1}$	–	–	-0.148*
			(0.024)
GDP per capita$_{t-1}$[1]	–	–	0.140*
			(0.055)
Polity2$_{t-1}$	–	–	0.080*
			(0.008)
t	17.486*	-0.110*	14.277
	(8.245)	(0.056)	(7.738)
t^2	-1.512	-0.007	-0.885
	(0.936)	(0.007)	(0.817)
t^3	0.043	0.001*	0.009
	(0.040)	(0.0004)	(0.031)
Constant	315.65*	-0.884*	-128.40*
	(86.084)	(0.217)	(45.501)

Number of observations: 63,163

Akaike Information Criterion: 21,693.97

* indicates $p < 0.05$.

Values in parentheses are standard errors clustered by player and bootstrapped using 1000 iterations.

$U_b(A\neg F)$ is the reference node and was normalized to zero.

[1] Natural log

Table 3.8: Player Utilities for Raids and Defenses, 1998-2008, With Military Expenditure

	$U_r(AF)$	$U_b(AF)$	$U_r(SQ)$
Cropland	1.376*	–	–
	(0.324)		
Wheat Yield	–	0.189*	–
		(0.074)	
Population[1]	-2.257*	-0.108*	–
	(0.556)	(0.017)	
GCP[1]	-5.856*	-0.139*	–
	(1.376)	(0.024)	
Terr. Change	23.231*	0.568*	–
	(3.224)	(0.174)	
Travel Time[1]	-2.066*	-0.045*	–
	(0.830)	(0.023)	
Border Distance[1]	-0.914*	-0.012	–
	(0.297)	(0.008)	
Temperature	0.729*	0.020*	–
	(0.131)	(0.004)	
Precipitation[1]	-3.871*	-0.126*	–
	(1.029)	(0.022)	
Conflict$_{t-1}$	–	–	-0.145*
			(0.021)
GDP Per Capita$_{t-1}$[1]	–	–	0.257*
			(0.055)
Polity2$_{t-1}$	–	–	0.056*
			(0.008)
Mil. Exp$_{t-1}$	–	–	-0.280*
			(0.029)
t	3.578	-0.092	4.578
	(6.560)	(0.125)	(6.453)
t^2	0.568	-0.009	0.361
	(0.938)	(0.021)	(0.901)
t^3	-0.062	0.001	-0.051
	(0.045)	(0.001)	(0.042)
Constant	-82.572*	2.713*	-78.229*
	(29.310)	(0.370)	(26.043)

Number of observations: 62,527

Akaike Information Criterion: 20,303.92

* indicates $p < 0.05$.

Values in parentheses are standard errors clustered by player and bootstrapped using 1000 iterations.

$U_b(A\neg F)$ is the reference node and was normalized to zero.

[1] Natural log

Table 3.9: Player Utilities for Raids and Defenses, 1998-2008, Baseline Model

	$U_r(AF)$	$U_b(AF)$	$U_r(SQ)$
Cropland	1.529*	–	–
	(0.309)		
Wheat Yield	–	0.283*	–
		(0.071)	
Population[1]	-2.151*	-0.159*	–
	(0.615)	(0.020)	
Temperature	0.614	0.025*	–
	(0.161)	(0.004)	
Precipitation[1]	-1.831*	-0.108*	–
	(0.721)	(0.018)	
Conflict$_{t-1}$	–	–	-0.208*
			(0.027)
GDP Per Capita$_{t-1}$[1]	–	–	0.123*
			(0.042)
Polity2$_{t-1}$	–	–	0.075*
			(0.008)
t	6.767	0.008	-17.798
	(7.552)	(0.130)	(15.115)
t^2	-0.318	-0.044*	3.527*
	(0.921)	(0.021)	(2.101)
t^3	-0.005	0.003*	-0.189**
	(0.041)	(0.001)	(0.096)
Constant	-76.377	2.859*	61.260
	(45.476)	(0.337)	(36.381)

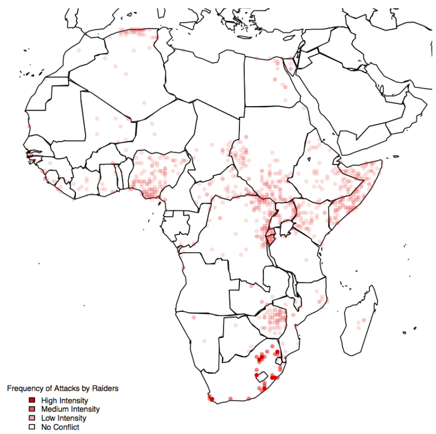
Number of observations: 62,527
Akaike Information Criterion: 20,307.26
* indicates $p < 0.05$.
Values in parentheses are standard errors clustered by player and bootstrapped using 1000 iterations.
$U_b(A\neg F)$ is the reference node and was normalized to zero.
[1] Natural log

Predictive Analysis

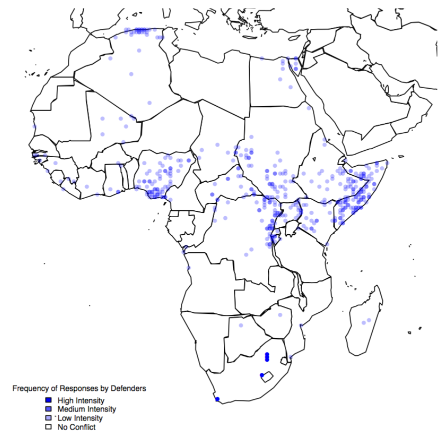
Statistical results can provide evidence about the incentives governing the strategic behavior of different actors, but these estimates in-and-of-themselves tell us little about the generalizability of this strategic model to out-of-sample situations, and whether the effects identified are truly substantively meaningful in a broader context (Greenhill, Ward and Sacks, 2011). Given the growing importance of forecasting to the study of political violence (Brandt, Freeman and Schrodt, 2011), a valid strategic model should also possess some *predictive power* that makes it preferred to a "coin-flip" model (i.e., a model that has a completely random chance of predicting a given conflict event). I evaluate the forecasting strength of the estimates derived by my strategic model for the years 1998-2008 on out-of-sample data for 2009-2010 (for summary purposes, the frequencies of raider attacks and defender responses for 2009-2010 are shown in Figure 3.4). To this extent, the separation plots in Figure 3.5 illustrate the strategic model's ability to forecast raids and defenses, respectively. These plots evaluate the model's predictive fit by showing the extent to which the actual instances of events (dark colors in these graphs) are concentrated on the right side of the plot, while instances of no-events (light colors) are concentrated on the left side (Greenhill, Ward and Sacks, 2011).

As these plots show, the strategic model does a reasonably good job of predicting conflict given that most of the events are clustered on the right-hand side of the graph. Indeed, the ROC curves for this model, reported in Figure 3.6, show that it correctly predicts approximately 84% of raider attacks (with a 95% confidence

Figure 3.4: The Regional Distribution of Attacks by Raiders and Responses by Defense Forces, 2009-2010

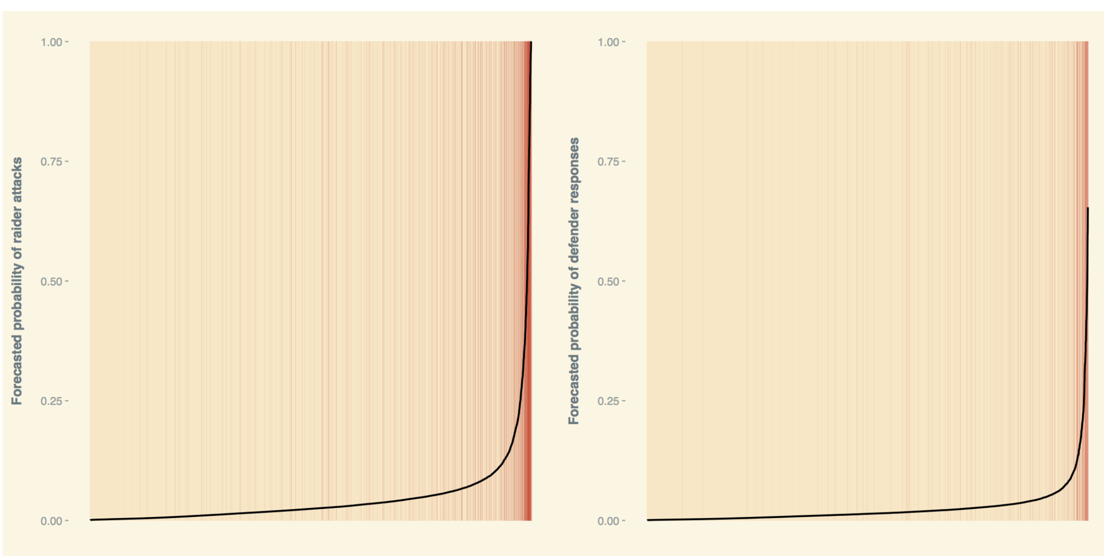


Raider Attacks, 2009-2010



Defender Responses, 2009-2010

Figure 3.5: The Forecasting Accuracy of the Statistical Strategic Model on Out-of-Sample Data, 2009-2010

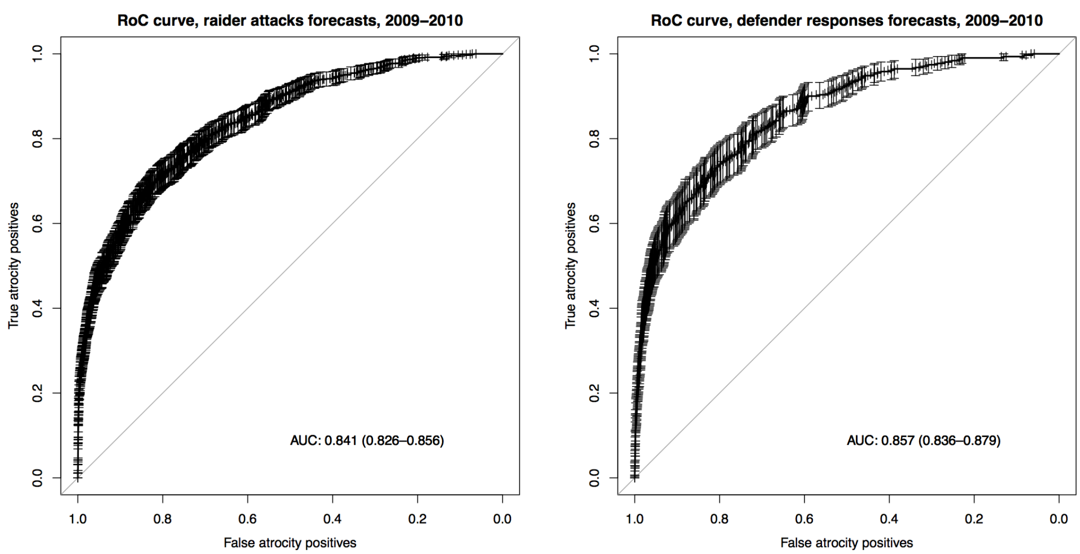


Foreasting Accuracy: Raids

Foreasting Accuracy: Responses

interval of 32% ⇔ 86%) and 86% of defender responses (with a 95% confidence interval of 84% ⇔ 88%) for the years 2009-2010. These quantities can be compared to the forecasting strength of a completely random "coin flip" model, which should correctly predict about 50% of all observations. Moreover, as additionally shown in Tables 3.10 and 3.11, this model provides a significantly better predictive fit to the data based on DeLong, DeLong and Clarke-Pearson (1988) test compared with standard logit models that do not account for the *strategic* nature of preemptive conflict (i.e., models that include all the regressors in one equation), using both in and out-of-sample data.

Figure 3.6: ROC Curves for Each Stage in The Statistical Strategic Model



Out-of-Sample ROC:
Raider Attacks, 2009-2010

Out-of-Sample ROC:
Defender Responses, 2009-2010

Note: The AUCs for each phase are ≈ 95% for raider attacks and ≈ 98% of responses by defense forces when the threshold is dichotomized at 0.5 instead of 1, as used by numerous studies that employ ROCs.

Table 3.10: Comparison of Prediction Strength, LQRM and Logit Models, 1998-2008

	Raider Attacks		Defender Responses	
	LQRM	Logit	LQRM	Logit
AUC	0.83	0.82	0.86	0.85
DeLong et al. test	$z = 5.373$*		$z = 4.787$*	
Favors:	LQRM		LQRM	
N	63,218			

Note: * indicates $p < 0.05$.

Null hypothesis for Delong et al.'s Test for two correlated ROC curves: true difference in AUC's is equal to zero.

Table 3.11: Comparison of Prediction Strength, LQRM and Logit Models, Out-of-Sample Data (2009-2010)

	Raider Attacks		Defender Responses	
	LQRM	Logit	LQRM	Logit
AUC	0.84	0.83	0.86	0.83
DeLong et al. test	$z = 2.234$*		$z = 3.602$*	
Favors:	LQRM		LQRM	
N	14,420			

Note: * indicates $p < 0.05$.

Null hypothesis for Delong et al.'s Test for two correlated ROC curves: true difference in AUC's is equal to zero.

In sum, the empirical model makes correct predictions for the vast majority of violent conflict events. Along with the theoretical model and qualitative evidence provided in the above, this provides strong indication that preemptive conflict over food resources is an important aspect of warfare in the developing world.

Conclusion

The use of food denial as a weapon is not a recent phenomenon. Throughout history and well into the 19th century, armies living off the land have been a regular characteristic of warfare, and—correspondingly—the preemptive destruction of food resources. By incorporating the insight that food support is crucial in facilitating military operations in these contexts and using a statistical estimator that is the structural equivalent of my theoretical model, this chapter confirmed these expectations at the highly localized level. These interesting findings diverge from current conceptualizations of food and violence in some prominent studies (e.g., Burke et al., 2009), but are consistent with a broad historical narrative and other studies of such attacks (Butler and Gates, 2012; Adano et al., 2012; Koren and Bagozzi, 2016).

This chapter, and the previous one, establish that food abundance impacts conflict patterns at the highly localized level. In both chapters, I developed different theories and derived relevant expectations that were then tested empirically using different methodological approaches. Both chapters could be viewed as stand-alone analyses, yet together they provide ample evidence not only that food matters as a generator and a compounder of conflict, but also *how* the two types of conflict—possessive and preemptive—are linked. To this end, I discussed and evaluated different relevant mechanisms that operate at the microlevel in contemporary warfare in Africa. What is still missing, however, is an answer to the question of how food resources impact broad rebellion patterns. In other words, how do the microlevel linkages between food resources and conflict identified in this present chapter and the previous one affect the likelihood and duration of rebellions at the macrolevel? Building on the insights developed in Chapters 2 and 3, the next chapter answers this question by using mixed microlevel evidence to derive and test macrolevel hypotheses. Nevertheless, as I discuss in great detail in the concluding chapter, independently, Chapters 2 and 3 nevertheless inform both our understanding of the causes of conflict, and how policymakers should approach these issues locally.

Chapter 4: Food and Rebellion – Evidence From Micro and Macro Level Analyses

Introduction

In Chapter 1, I constructed a theory linking food resources abundance to social conflict and civil war in developing countries. I described how armed groups derive strategies according to food security concerns, and how issues of local food availability and access explains not only how conflict arises locally, but also how it affects (i) the distribution of violence within the state, and (ii) armed conflict outcomes. Broadly, rebellions cannot succeed if access to locally-produced food resources does not exist, *or persist*. Nor can rebellions be quashed if armed groups cannot guarantee and protect local food support networks that allow these organizations to operate in different regions for long periods of time. Although modern armies of developed countries are likely to enjoy regular logistic support, such assistance is relatively rare in the developing world, especially for rebel and militia groups (Henk and Rupiya, 2001). Access to locally sourced food is thus crucial in facilitating the success of a rebellion; the ability of different armed actors to control key food provision points is paramount.

In Chapters 2 and 3, I developed and tested complementary, microlevel explanations to scarcity-centric theories by highlighting two broad types of conflict over food security associated with the local *abundance of food resources*. In Chapter 2, I showed that groups frequently initiate conflict locally in order to secure food resources for their own consumption, a strategy I called *possessive conflict* over food security. In Chapter 3, I derived a statistical strategic model to show that armed groups fight over food resources not only to possess them but also to prevent them from being consumed by others, and to illustrate that local conflict frequently arises *endogenously*, as a result of the strategic choices made by different groups. I accordingly termed this interaction *preemptive conflict* over food security. By integrating novel theoretical explanations with quantitative empirical analysis, these substantive chapters established that the abundance of food resources have a strong impact on conflict, both within and outside of rebellion confines. This is a counterintuitive finding, given previous scholars' understanding of food production as impacting conflict primarily through increasing local scarcities, which generate stronger competition and reduce economic output (e.g., Burke et al., 2009; Miguel, Satyanath and Sergenti, 2004).

Accordingly, the present chapter connects the arguments developed and analyses conducted in Chapters 2 and 3 to the broad framework proposed in Chapter 1. In the first part of this chapter, I corroborate these claims through a meticulous mixed-methods analysis of the Mau-Mau rebellion in 1950s Kenya, which employs archival records originally collected in the National Archives of the United Kingdom. These microlevel analyses allow me to derive two research hypothesis for how food availability should impact conflict patterns at the *macrolevel*. Accordingly, in the second section of this chapter I test these hypotheses on a sample of all countries over the 1961–1988 period. In both analysis stages I confirm that food resources significantly and substantively increase both the probability of rebellions, and their duration. I then estimate an extensive number of sensitivity analysis to illustrate not only the robustness of my analyses, but also the applicability of this theory to contemporary times. Finally, I conduct a set of two-step probit instrumental regressions to illustrate that my results are reasonably robust to endogeneity concerns.

The Mau Mau Rebellion: A Disaggregated Analysis

In this section I report on a microlevel, mixed-methods analysis conducted using data I collected and coded on the Mau Mau rebellion in Kenya to evaluate the validity of my theoretical expectations and set them in a historical context. The documents used throughout this section for both the qualitative and quantitative analyses were collected at the National Archives of the United Kingdom. Some of these records have only become available within the past few years. Due to the exceptional level of detail found in these documents, the Mau Mau case is instrumental in illustrating the critical nature of food resource accessibility in the context of armed rebellion. Because the strategic decisions and deliberations of policymakers are extremely well-documented, it is possible to distinguish between the physical and psychological aspects of regular food support. Qualitatively, I rely on documents written by British colonial administrators to show that these officials were aware of both the physical wellbeing and morale-building aspects of regular access to *nutritious* food, and thus sought to limit the rebels' food access, forcing them to spend most of their time hunting or foraging and simultaneously lowering their morale. Quantitatively, I validate whether the behavior of Mau Mau rebels followed the patterns one would expect based on these qualitative sources using an original district-month dataset on different types of violence occurring locally within three Kenyan districts, and accounting for a variety of confounders.

Background

The Mau Mau rebellion that began in 1952 was one of Britain's most violent decolonization wars (Bennett, 2013). The Colony and Protectorate of Kenya, originally the East Africa Protectorate, had been a British colony since 1895, although private companies operated in the region since the 1840s. The conflict all but ended in 1956, after the rebel leader Dedan Kimathi was captured and executed, although limited skirmishes and small-scale raids continued to occur until the end of the decade. Casualty estimates for the rebellion, including both combatants and civilians, range from 5,000 to 20,000 deaths (Bennett, 2013, 18–19). It was a brutal rebellion involving severe human rights violations by both British and Mau Mau troops (Branch, 2007). British counterinsurgency operations were extensive and included the fortifications of villages and police posts, large-scale raids and patrols, widespread imprisonment of suspects in transitional camps, and even civilian killings and witch-hunting of Mau Mau oath-takers (Luongo, 2006).

Grievances, especially those related to agriculture and the distribution of land, were a major motivation for the rebellion. During the war, many Kikuyu, Embu and Meru—the major ethnic groups in Kenya—were pushed to join Mau Mau because they were excluded from the means of achieving self-sustenance within the colonial political economy by settler farmers, colonial administrators, and other "land-hungry" patrons (Branch, 2007). Even prior to the rebellion, these aggrieved individuals rejected the leadership of chiefs within their respective groups, men who in practice served as local administrators under the colonial regime, by refusing to obey and sometimes even directly attacking them. The politics of protest also became radicalized, especially after those who served in the British armed forces during the Second World War returned to Kenya. Having served overseas, these veterans rejected the belief, encouraged by the British, that a European is better than an African (Branch, 2007).

The Mau Mau rebellion started as a low-intensity conflict, with sporadic attacks against local chiefs and police stations (Bennett, 2013). With security forces stretched thinly across the region and the loyalist auxiliary Home Guard poorly organized, however, the majority of Kenyans could not be protected from Mau Mau and related violence. As a result, the low-intensity emergency quickly morphed into a full-scale civil war, with the Mau Mau escalating both the number and scale of its attacks, and adding British military forces and European farmers to its list of targets. The Mau Mau initiated loyalty oaths, which many civilians—even if they did not support the rebellion's aims—took as to avoid being labeled as loyalists (Branch, 2007). The Mau Mau, however, did not always resort to terror to obtain support. Its appeal to widespread grievances, especially the desire to expand access to land and food resources, made Mau Mau a popular cause so long that there was no viable alternative. Violence against civilians was used more to gain the begrudging endorsement of waverers and guarantee compliance, or to influence European farmers (Branch, 2007).

The British response was initially unsuccessful. Massive waves of arrests failed to halt the violence, and patrols and raids achieved no tangible results. This led many to criticize the colonial government as having no real strategy to handle the increasingly violent rebellion (Bennett, 2013). Slowly, British military retaliation gained momentum. More local police guards were hired, and arrests became more effective at weakening the Mau Mau. The British also started a system of "screening camps," designed to weed out Mau Mau oath takers and other supporters. At the same time, Mau Mau attacks became more violent. On March 26, 1953, the Mau Mau attacked both Lari village and the Naivsha police station. In Lari, the Mau Mau massacred 120 civilians, while the raid on Naivsha resulted with the release of many prisoners and the loss of weapons and munitions, which heavily embarrassed the government (Bennett, 2013, 17-18). The British responded by heavy arming of the Home Guard and the deployment of the Buffs and Devons brigades, which signaled to beginning of an organized counterinsurgency campaign.

Analysis

Shortly after the beginning of the rebellion, colonial officials came to recognize that regular access to food both provided easy fuel to the Mau Mau, and served to boost the rebel troops' morale. These officials thus sought to *systematically* limit the rebels' access to locally sourced food, drawing on the active participation of provincial governors, district committees, the army, and local farmers (Bennett, 2013, 255-257).[1] As guided by the high command, army forces and farmers prematurely harvested crops deemed particularly valuable for the Mau Mau, such as maize and potatoes. Between May and June 1953, the army reaped about 400 bags of potatoes, while units began clearing "shambas" (farms or plots of lands), preventing crops from being planted close to the forest, concentrating labor near

[1]For a similar counterinsurgency strategy in Malaya, see Ramakrishna, 2002, 140-143.

farms, and enclosing cattle in "bomas," or pens. These food denial measures were intended both to reduce the physical capacity of Mau Mau rebels, and lower their morale. Indeed, both aspects were mentioned in an edition of the *East African Standard*, the most widely read newspaper in Kenya and strongly pro-colonial, from June 1953, which stated that, "the plan has the intention of making the gangs spend their time and energy searching for food so their raids and killings are cut down; and at the same time lower their resistance powers and morale as the offensive is stepped up by striking forces."[2]

The same dual logic was apparent in policymaking deliberations. For instance, the committee responsible for limiting rebel access to food around the Aberdare mountain range recognized that Mau Mau rebels operating in the region "could, if so compelled, subsist on game and the natural resources of the forest. For example, a buffalo cuts up at about 1500 lbs of meat: assuming that the Mau Mau gangs number approximately 700 men, an average of one buffalo a day would, statistically, suffice to feed them."[3] However, they believed that limiting rebels' access to food grown by local farmers would nevertheless be an advantageous strategy, because, "[a]lthough the gangs could live on the natural produce of the forests, the Committee consider that if they were forced to do so, their efficiency for operations would be much reduced; they would have to spend so much time and energy in feeding themselves that they would be much less formidable opponents than they are now. It is therefore worthwhile trying to deprive them of supplies which are more easily obtainable."[4]

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[2]"GANGS BEGIN TO FEEL THE PINCH: Food supplies denied them." *The East African Standard*, June 25, 1953.

[3]Document 7, The National Archives, Foreign and Commonwealth Correspondence and predecessors (FCO), series 141/6201.

[4]Ibid.

The decision to impose food denial measures proved effective very quickly. As Bennett—author of arguably the most authoritative study of the Mau Mau rebellion from a military perspective—succinctly summarizes, "by mid-September [1953] Mau Mau redeployments favourable to the security forces appeared to be caused by food denial," and as a result, "the 39 Brigade placed greater emphasis on the policy, making it the second priority, after destroying gangs" (2013, 256). Senior military officials were quick to recognize the important role food denial played in their grand counterinsurgency strategy, so much that "[o]ver the summer of 1955 the new Commander-in-Chief of the British forces, Lieutenant-General Lathbury, took a direct interest in food denial, meeting farmers to explain the policy's rationale" (Bennett, 2013, 256). Many British units stepped up their food denial operations to guarantee that when the Mau Mau attacked, the army would be ready. For instance, the "49th Brigade placed food denial on the same footing as destroying gangs in late February 1955, when gangs were dispersed and depended on stealing food to survive. The hope was that starving Mau Mau would attack farms in a desperate bid to survive" (Bennett, 2013, 256).

To broadly evaluate these predictions, I construct a geocoded, within-country district-month dataset for three contingent districts for which enough data and documentation were available as to code a relatively large number of cases. These districts, Kajido, Machakos, and Narok, were part of the large "native reserve" located on the southern part of the state (see Figure 4.1, appendix), and experienced some of the highest rates of Mau Mau activity, conflict, and arrests, at least partly due to their mixed ethnic composition of Masai and Kikuyu. Using detailed archival resources on casualty statistics by location (also obtained from the National Archives), I created three dependent variables coded for each month starting January 1952 and ending December 1956. The first variable codes all violent events recorded in the data; the second variable codes a subset of these incidents that involved only armed conflict events occurring between combatants; and the third variable codes a subset of these incidents that involved only attacks perpetrated by Mau Mau rebels against civilians.

To test how each of these dependent variables was affected by the level of access to food resources across these three districts, i.e., where staple crops are grown over more area and hence could be more easily obtained, I created a variable, *Cropland*, measuring the total area equipped for irrigation within each region (in hectares) (Siebert et al., 2015), in a manner used in past research (e.g., Koren and Bagozzi, 2016). Understandingly, the availability of geospatial and environmental data from the period in Kenya—and Africa more broadly—is very limited, especially at the *localized* level. However, these localized data on irrigated land at the highly disaggregated 0.5 x 0.5 degree resolution level are available for 1950 and were aggregated to the district level to create this explanatory variable. While a time-varying indicator of food crops at a similar level of aggregation was not available for these locations and years, using pre-conflict values should help account for some potential endogeniety concerns. With the implementation of food denial measures everywhere in the three regions analyzed, lagged localized data on irrigation provide a good proxy for locations where crops and cattle were available over wider areas—even after food denial measures were implemented. Indeed, this is supported by the analyses conducted in Chapter 3, which similarly relied on a constant measure of localized food crop yields to illustrate that raiders are

Figure 4.1: Administrative Areas Affected by the Uprising

Source: Bennett (2013)

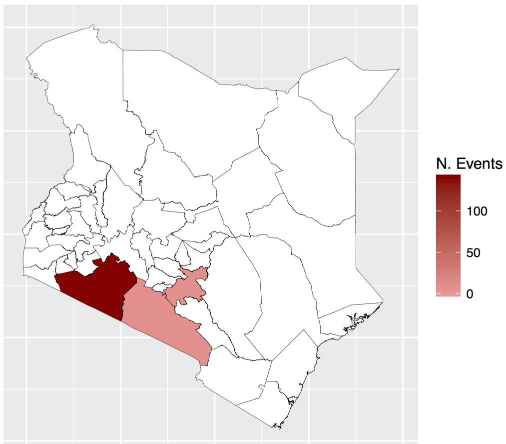
significantly more likely to attach food abundant regions during conflict. As they are constant for the time period of concern, these data capture not only within-district effects, but also the impact of troops moving between the three contingent districts, a crucial factor when the importance of access to locally sourced food and the mobility of rebel groups are taken into account.

Despite the poor availability of geolocated data in Kenya for the early 1950s, I was able to include several important district-level controls in my analysis. First, to account for the possibility that violence resulted from shocks to local food availability, which can increase pressures on available resources and might lead to violence (Miguel, Satyanath and Sergenti, 2004), I include an annual indicator measuring drought levels, *Drought*. This variable codes the annual proportion of months that are part of the longest streak of consecutive months where precipitation values were -1.5 or more standard deviations below the mean (out of 12 months) (Beguería et al., 2014).[5] Second, to verify that *Cropland* indeed captures the effect of higher food access rather than operates as a proxy for population densities, I include a control measuring the number of persons within a given district for 1950 (Klein Goldewijk et al., 2011).[6] Third, to control for continuous violence trends from one month to the next, a one-month lag of the dependent variable is included in the models. Finally, to account for month- or year-specific factors, as well as temporal dependencies of conflict more broadly, binary variables for each month and year, respectively, (i.e., month and year fixed effects) were also included in each regression. For illustration purposes, the variation in conflict events, violence against civilians, irrigated land, and drought levels for each district over the entire period are plotted in Figure 4.2. Additionally, summary statistics of all variables used in this analysis are reported Table 4.1.

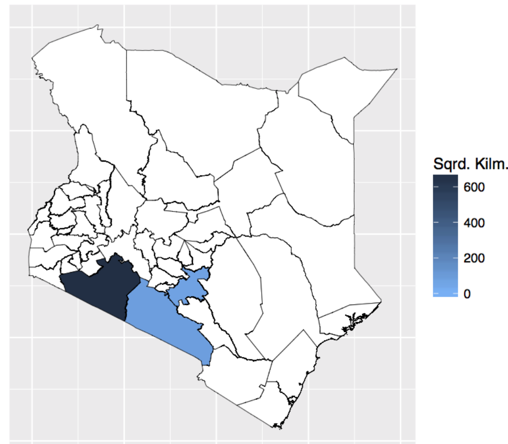
[5] Like *Cropland*, this variable was measured at the 0.5 x 0.5 degree grid and averaged to the district level.

[6] This variable was originally measured at the 0.5 x 0.5 grid cell level. Note that these data are not available for Kenya prior to 1970. For each 0.5○ grid cell, values for 1950 were extrapolated based on information available for the 1970-2000 period, and the total of these results were aggregated by district. The results remain unchanged when real values for 1970 are used.

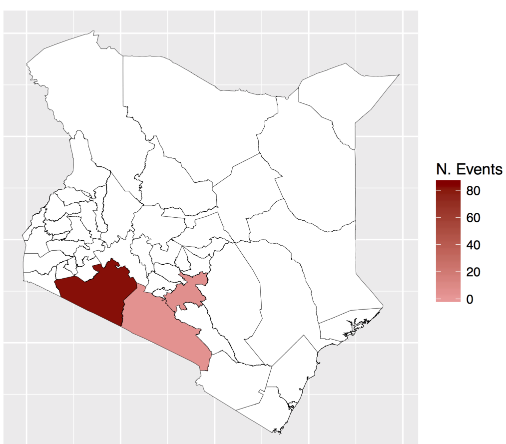
Figure 4.2: Maps of Violence, Cropland, and Drought Levels for the Kajido, Machakos, and Narok Districts



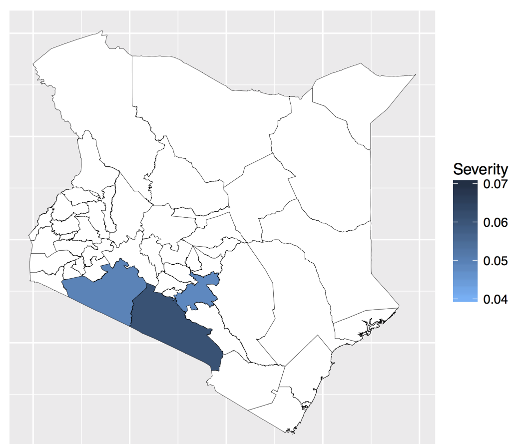
All Conflict Events



Cropland



Violence Against Civilians



Drought Severity

Table 4.2 reports the estimates of different negative binomial (NB) models used to assess how violence within the three districts mentioned above was distributed spatially during the rebellion. Each specification was estimated separately on each

Table 4.1: Summary Statistics of Microlevel Analysis Variables

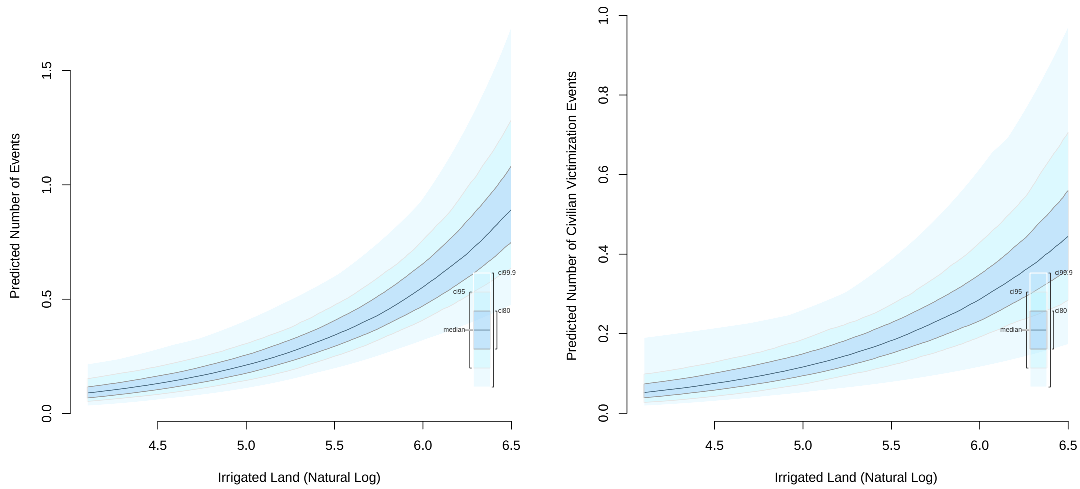
	Minimum	Median	Mean	Max	SD
Conflict	0	0	0.887	20	2.468
Armed conflict	0	0	0.367	5	1.003
Civilian victimization	0	0	0.520	15	1.689
$Conflict_{t-1}$	0	0	0.881	20	2.469
$Armed\ conflict_{t-1}$	0	0	0.362	5	1.002
$Civilian\ victimization_{t-1}$	0	0	0.520	15	1.689
Cropland[1]	4.100	4.340	4.983	6.509	1.087
Drought	0.010	0.063	0.053	0.104	0.029
Population[1]	12.462	13.584	13.261	13.736	0.570

[1] Natural log

of the three different dependent variables. The Baseline model includes only the main explanatory variable *Cropland* in addition to fixed effects by month and year to illustrate that the any observed relationships are not the results of adding different controls. Across all models and specifications, the coefficient of *Cropland* is significant (to a $p < 0.01$ level) for each of the three dependent variables. This confirms the argument that localized violence during the Mau Mau rebellion was significantly more frequent in areas that prior to the rebellion offered more access to locally sourced food. Importantly, other factors such as variations in drought severity or population densities, as well as month- or year-specific factors (e.g., harvest month), do not have a consistent effect on all three dependent variables across all models.

Substantively, Figure 4.3 shows the predicted change in the frequency of all conflict events and civilian victimization, specifically, for the Full model across the entire range of *Cropland*, when all other variables are held to their mean values (estimates were calculated based on repeated 1,000 simulations). The total number of conflict incidents increased by approximately one incident per month, on average, across the entire range of irrigated land in the Full model, while the number of civilian victimization events, specifically, increases by approximately 0.4 incidents per month, on average. Considering that the average number of all violence events in a given district for each month in this dataset is ~ 0.9 while the number of civilian victimization incidents is ~ 0.5, this effect is sizable. These quantitative findings thus strongly support the expectation that, during ongoing rebellions, violence dynamics should be positively associated with more access to locally sourced food. They also suggest that the more recent conflict patterns identified in Chapters 2 and—to a certain extent—Chapter 3 also characterized the Mau Mau rebellion. Indeed, these microlevel analysis results combined with qualitative archival evidence suggest that areas with more access to food experienced higher levels of all violence types by forces moving in or otherwise initiating conflict and other attacks to obtain food, as was argued in Chapter 2, while the British defense forces sought to control these access points, which also lead to more conflict, as was shown in Chapter 3.

Figure 4.3: Predicted Probability and Violence and Civilian Victimization in Kajido, Machakos, and Narok



Conflict Civilian Victimization

To ensure that food denial measures produced "maximum squeeze"[7] on the Mau Mau, colonial officials placed the highest priority on limiting access to those food resources considered especially valuable, nutritious, and vulnerable to theft. For instance, the Rift Valley committee stated that, "[t]he following crops of value to the terrorists, i.e. maize, potatoes and sweet potatoes may not be grown within 3 miles of the edge of the Aberdares forest."[8] This in contrast to wheat, which was grown primarily by European farmers. As a result, it was easier to prevent the theft of wheat, and to quickly harvest wheat fields if needed. In the later part of 1955, for instance, colonial officials successfully removed 441,000 bags of wheat

[7]Document 73, The National Archives, Foreign and Commonwealth Correspondence and predecessors (FCO), series 141/6202.

[8]Document 48, The National Archives, Foreign and Commonwealth Correspondence and predecessors (FCO), series 141/6201.

Table 4.2: Violent Events in Three Kenyan Districts, 1952-1956

	Baseline			**Medium**			**Full**		
	Conflict	**Armed com.**	**Civ. vict.**	**Conflict**	**Armed com.**	**Civ. vict.**	**Conflict**	**Armed com.**	**Civ. vict.**
Cropland[1]	1.245***	1.117***	1.338***	1.049***	1.124***	1.063***	1.070***	1.115***	1.108***
	(0.188)	(0.225)	(0.262)	(0.201)	(0.257)	(0.278)	(0.227)	(0.290)	(0.316)
DV_{t-1}	–	–	–	0.146***	0.115	0.319***	0.146***	0.115	0.319***
				(0.041)	(0.130)	(0.080)	(0.041)	(0.130)	(0.080)
Drought[1]	–	–	–	5.922	11.067	4.024	5.922	11.067	4.024
				(6.928)	(9.686)	(9.051)	(6.928)	(9.686)	(9.051)
Population	–	–	–	–	–	–	−0.302	0.120	−0.643
							(0.498)	(0.709)	(0.682)
Constant	−7.926***	−7.861***	−9.480***	−7.024***	−8.210***	−7.982***	−3.011	−9.807	0.562
	(1.299)	(1.548)	(1.826)	(1.448)	(1.881)	(2.005)	(5.740)	(8.494)	(7.674)
Observations		177			177			177	
Log Likelihood	−149.411	−90.043	−113.571	−144.368	−88.878	−106.895	−144.368	−88.878	−106.895
Akaike Inf. Crit.	334.822	216.086	263.141	328.737	217.755	253.791	328.737	217.755	253.791

* indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$.
Variable coefficients are reported with standard errors clustered by district in parentheses.
Fixed effects by month and year included in each regression, although not reported here.

[1] Natural log

to safe storage, where—a durable crop as it was—it could be kept for future use.[9] Indeed, the biggest problem with controlling the distribution of wheat was not its popularity among Mau Mau rebels or the lack of compliance by reluctant farmers, but rather "the bottle neck over this at present is the Railway whose supply of bogies is unsatisfactory."[10]

By June 1953, guards and police in so-called "squatter shambas"—i.e., plots of land where local Kenyans, mostly from the Kikuyu ethnic group, lived as hired or temporary labor—were ordered to, "keep and protect in stores at the homestead all squatter maize, beans, etc., and that squatters should draw their requirement daily from these stores."[11] In 1955 it was declared that, "[n]o potatoes, no maize, and no squatter stock will be permitted on a farm where there is normally no resident European."[12] As late as February 1956, when violence had largely subsided, military and police forces were instructed to remove potatoes and maize from local villages, and several councils ordered that no maize will be grown in their respective districts.[13] Frequently, forced laborers were employed in removing crops and clearing brush within one to five mile of the forest.[14]

Preventing the rebels from accessing maize supplies, specifically, was important for two reasons. First, a high-protein, high-starch crop, maize provided ample

[9]Document 161/1, The National Archives, Foreign and Commonwealth Correspondence and predecessors (FCO), series 141/6202.
[10]Document 88/1, The National Archives, Foreign and Commonwealth Correspondence and predecessors (FCO), series 141/6202.
[11]Document 21, The National Archives, Foreign and Commonwealth Correspondence and predecessors (FCO), series 141/6201.
[12]Document 176, The National Archives, Foreign and Commonwealth Correspondence and predecessors (FCO), series 141/6201.
[13]Document 61, The National Archives, Foreign and Commonwealth Correspondence and predecessors (FCO), series 141/6202.
[14]Document 93, The National Archives, Foreign and Commonwealth Correspondence and predecessors (FCO), series 141/6202.

caloric intake, which—combined with the crop's long durability—meant maize was the most energy efficient crop Mau Mau rebels could obtain. Because it grows tall and thick, maize also allowed the rebels to more easily conceal themselves when moving out of the forest to capture other resources. For instance, in April 1955 colonial officials published "an Emergency Regulation forbidding the planting of maize...since this crop when planted amoung potatoes affords cover for the easy removal of the potatoes" (*sic.*).[15] Second, the main staple among the Kikuyu (Kanogo, 1987, 112), maize was the "major food and cash crop" in Kenya (Kanogo, 1987, 19), especially for "squatter" farmers. By selling it externally and getting high prices, these farmers acquired socio-economic value as independent producers during the inter-war period, when the British authorities overall increased their control over the "squatter" population (Kanogo, 1987, 55-59). Indeed, the colonial officials were aware of the relative popularity of maize and its importance compared with other staple crops to many Kenyans. For instance, in January 1954, the Central District provisional commission commented that "[i]t was considered undesirable to prohibit the 'long rains' planting of maize since...[i]t would tend to lead to a mass civil disobedience campaign on the part of the women; cases occurred in 1953 in South Tetu when short rains planting of maize was forbidden."[16]

For the Mau Mau rebels, maize both offered the greatest nutritional "bang for buck" as a calorie- and protein-rich staple crop that could feed a large number of troops for a long period of time. Maize was also relatively prevalent in regions where the Mau Mau could operate with relative ease, or territories where Kikuyu—

[15]Document 88/1, The National Archives, Foreign and Commonwealth Correspondence and predecessors (FCO), series 141/6202.

[16]Document 60, The National Archives, Foreign and Commonwealth Correspondence and predecessors (FCO), series 141/6201.

many of whom were supportive of the Mau Mau's aims—lived. Maize is thus an example of a staple crop that encapsulates the maximal level of *efficiency* troops can extract from the food resources available to them, and—correspondingly—to their ability to fight a continuous war. Moreover, as Figures 4.4–4.5 below show, maize was rather prevalent in rebellion-afflicted countries during the same time period. As far as the Mau Mau rebellion is characteristic of other, similar rebellions, it suggests that food is an important—and yet under-analyzed—factor influencing the likelihood and duration of such conflicts. This begs the question: How applicable are the relationships identified here to other, similar rebellions? In other words, how do the patterns observed at the local level translate to macrolevel outcomes?

The theoretical framework developed in Chapter 1 and the qualitative and quantitative evidence presented in this section suggest that the prevalence of nutritious food crops facilitates rebellions by allowing rebel groups to recruit, substantiate their size, and even attract individuals due to food-related grievances (Hendrix and Brinkman, 2013). Higher access to these resources should also enable rebel groups to fight for longer periods of time by ensuring their troop are well sustained, which increases the group's credibility to its members, and helps to guarantee that these troops will fight together toward a common goal. Moreover, as I have shown in Chapter 2, rebellions occur primarily in countries with relatively low levels of development, where the majority of individuals—including combatants and potential recruits—depend on locally grown food. In these low development contexts, the marginal returns from an additional kilogram of staple crops such as maize available per capita were—on average—quite high (Food and Agricultural Organization of the United Nations, 2013). This suggests that if one wishes to identify macrolevel linkages between food resources and conflict, relying on staple crop-based indicators should, from a theoretical perspective, provide the most observable effects. Building on the quantitative and qualitative evidence presented in this section and this chapter's broader theoretical argument, the first generalizable hypothesis accordingly assumes that access to more nutritious staples should facilitate recruitment and cohesion among rebel groups:

- Hypothesis H1: The likelihood of rebellions should increase in countries and years where more nutritious crops are available per capita

Moreover, in addition to facilitating recruitment and enabling rebel groups to increase their relative size and elicit member participation, higher availability of nutritious staples should also allow these groups to fight for longer periods by providing them with both the necessary fuel to support members, and the ability to credibly illustrate their resilience to their members. This increases internal group cohesion and commitment to a shared goal, which accordingly suggests a second, related hypothesis:

- Hypothesis H2: Ongoing rebellions should last longer in countries and years where more nutritious crops are available per capita

Macrolevel Analysis: Global Evidence on Rebellions, 1961-1989

Data

These two hypothesis are tested on a sample encompassing 28 years (1961–1988), during which 64 countries experienced civil and anti-colonial war episodes, or rebellions. Because I relied on a mixed-methods case study of a rebellion from the Cold War period to test my theoretical argument at the micro level, I chose this temporal period specifically as to maintain the integrity of my empirical macrolevel analysis; ensure—from an empirical perspective—that the sample analyzed likely exhibits similar patterns to those observed in 1950s Kenya; and verify that the staple crop type tested is the same crop spotlighted by the documents discussed above. 1961 was the first year for which specific data on food production by country were available from the Food and Agricultural Organization of the United Nations (FAO), while 1988 was chosen as the final year before the 1989 Revolutions, the fall of the Berlin Wall, and the end of the Cold War. This temporal period thus corresponds to conflicts characteristic of the Cold War, which were broadly similar to the Mau Mau rebellion, i.e., internal wars frequently fought against relatively well-armed adversaries—colonial occupiers or others—within the context of low development (where the impact of locally sourced food is likely to be the most acute), and involve the active or passive interferences by Great Powers (Fearon, 2004).[17] Moreover, considering that many of the studies on the relationship between climate and conflict focus on the temporal period after 1980 – i.e., period when the effects of climatic variability become strongly more noticable (Guha-Sapir, Below and Hoyois, 2015) – the reliance on earlier decades also allows me to separate the effect of food from that of climatic variability more broadly, and to set it within a more historical context. Nevertheless, to show that the theory developed here is applicable to contemporary rebellions, robustness models estimated on an extended sample that covers the entire 1961-2011 period are reported in Table 4.6

[17]Some examples include the Portuguese Colonial Wars (1961-1974), Nigeria (1967), Ethiopia (1974), and Algeria (1954).

below.

Global data on rebellion were obtained from the UCDP/PRIO Armed Conflict Dataset Version 4-2016 (Melander, Pettersson and Themnér, 2016; Gleditsch et al., 2002), which records all conflicts between two parties—one of which is an official state government—that resulted in at least 25 combatant deaths. After creating a subset of conflicts that occurred specifically within my temporal period of interest, I removed any wars recorded as occurring only between two or more states to focus specifically on extrasystemic, internal, or internationalized-internal armed conflicts. The resulting dependent variable, *Rebellion*, is a binary indicator, measuring whether a rebellion was recorded as ongoing (coded one) or not (coded zero) within a given country during a given year, with a mean of 0.149 and a mode of zero.

To test hypotheses H2, I then create a subset of these data, which includes 65 countries reported as having an ongoing rebellion (including years where the rebellion began and ended), i.e., countries where the variable *Rebellion* took a value of one. This resulting subset is then structured into a survival analysis framework, where the observations are the years during which each rebellion episode was recorded as ongoing by the UCDP/PRIO Armed Conflict Dataset Version 4-2016. Accordingly, a second dependent variable, *Rebellion termination*, is operationalized as the final year during which a rebellion episode (as defined above) was observed in the UCDP/PRIO data. Termination was defined based on whether an event or a set of events (e.g., peace accords) occurred, or based on the final day/period when fatalities have been reported jointly (Melander, Pettersson and Themnér, 2016). Rebellions that were ongoing in 1989 were treated as right-censored. For summary purposes, the duration of the longest rebellion (in years) for each country experiencing an ongoing rebellion is reported in Figure 4.4.

To measure food availability, I rely on the annual production levels of maize for each country worldwide within the 1961-1988 period. Maize was chosen for several reasons. First, maize is a primary global staple, especially in developing countries (Food and Agricultural Organization of the United Nations, 2016, 2013), making it likely that—even without its other advantages and characteristics taken into account—a good choice to approximate statewide food availability. Indeed, maize is the main staple crop in Africa, Latin America, and western Asia, regions that historically were highly susceptible to rebellions (Oerke and Dehne, 2004). Second, maize fields are prevalent in many rebellion-prone countries, specifically, which means that they are likely to be the most accessible to a rebel group fighting in rural areas, which, as Mkandawire argues, "aspires to some form of sedentary existence or respite in 'liberated zones'" (2002, 200). As such, regular access to more maize fields should allow rebel leaders to credibly show that they can support their members and fight long conflicts, thus increasing group cohesion as the theory developed above suggests.

Third, unlike many other crops, maize can be easily retrieved, stolen, transported, and kept for relatively long periods of time without the risk of decomposition. Maize does not require special preparation or processing, and in fact can easily be consumed raw. It is also rich in both starches—i.e., energy—*and* nutritious proteins, fuel to support hungry rebels and their war efforts (FAO, 2013). Finally, as the qualitative evidence presented in the previous section shows, British colonial officials were particularly concerned about highly nutritious crops, and maize was the staple most frequently mentioned in these documents. Considering that when moving from micro- to macrolevel analysis I tried to maintain empirical coherence to the best of my ability (as I discussed above), relying on these primary documents to identify specific food resources that might be especially valuable to rebels in other contexts follows this very approach. For illustration, caloric intake from maize as percent of total caloric intake for all countries surveyed by the FAO are reported in Table 4.3. Nevertheless, to illustrate that my global analyses' findings are robust to this focus on maize, a robustness model that relies on an alternative conceptualization that incorporates all *nutritious* grain types is reported in Table 4.6 below.

Table 4.3: Maize As Total Caloric Intake For Selected Countries*

Country	Maize (kcal/capita/day)†	Total Intake (kcal/capita/day)‡	Maize % Total
Malawi	1,163.667	2,236.52	**34.224%**
Zambia	927.667	1,967.49	**32.042%**
Mexico	997.333	2,123.56	**31.957%**
Kenya	695.667	1.798.67	**27.890%**
Guatemala	793.667	2,289.96	**25.738%**
Timor-Leste	598.667	2,180.08	**21.544%**
Togo	569.667	2,158.96	**20.877%**
Mozambique	437.667	1,955.3	**18.290%**
Egypt	567.333	2,629.32	**17.748%**
Moldova	548.667	2,689.94	**16.941%**
Paraguay	519.667	2,836.87	**15.482%**
Venezuela	400.667	2,189.09	**15.471%**
Nepal	372	2,230.92	**14.292%**
Bolivia	291.333	1,866.47	**13.501%**
Uganda	242.667	2,006.2	**10.791%**
Mali	271.667	2,276.33	**10.662%**
Ghana	200.667	2,302.29	**8.017%**
Côte d'Ivoire	182.333	2,104.62	**7.973%**
Haiti	184.333	2,323.93	**7.349%**
Panama	158	2371.33	**6.247%**
Pakistan	110.667	1949.4	**5.372%**
Laos	131.667	2,570.84	**4.872%**
Cambodia	101.667	2,054.87	**4.714%**
Philippines	88.667	1,899.94	**4.459%**
Chad	102	2,461.29	**3.979%**
Viet Nam	84.667	2,115.88	**3.848%**
Thailand	93.333	2,617.22	**3.443%**
Azerbaijan	78	2855.55	**2.659%**
Niger	26.333	1,937.64	**1.341%**
Sudan	23	2,237.72	**1.017%**
Albania	20.667	2,924.91	**0.702%**
Hungary	5	2,449.92	**0.204%**
Bangladesh	3.667	2,119.18	**0.173%**
Lithuania	3.667	2,811.39	**0.130%**
Iraq	3	2,582.48	**0.116%**

* All countries in which the FAO conducted surveys

† Average, 2006-08 (FAO estimates)

‡ Data based on FAO surveys conducted in these countries, 1999-2008

Building on previous research on food security (e.g., Barrett, 2010), I code an indicator, *Maize (KgPC)*, that measures the total amount (in kilograms) of maize available per capita in each country over the temporal period of analysis. As such, this indicator measures food availability—i.e., supplies—as commonly conceptualized in extent research (e.g., Koren and Bagozzi, 2016), which are "typically measured in daily calories per person" (Barrett, 2010, 825). This indicator was obtained from the FAO (2016). For summary purposes, the average availability of maize by country in kilograms per capita is reported in Figure 4.5. Indeed, a visual inspection of Figures 4.4–4.5 shows that many of the countries experiencing the longest rebellions also had medium-to-high levels of maize production.

Figure 4.4: Conflict Duration (Years), 1961-1988

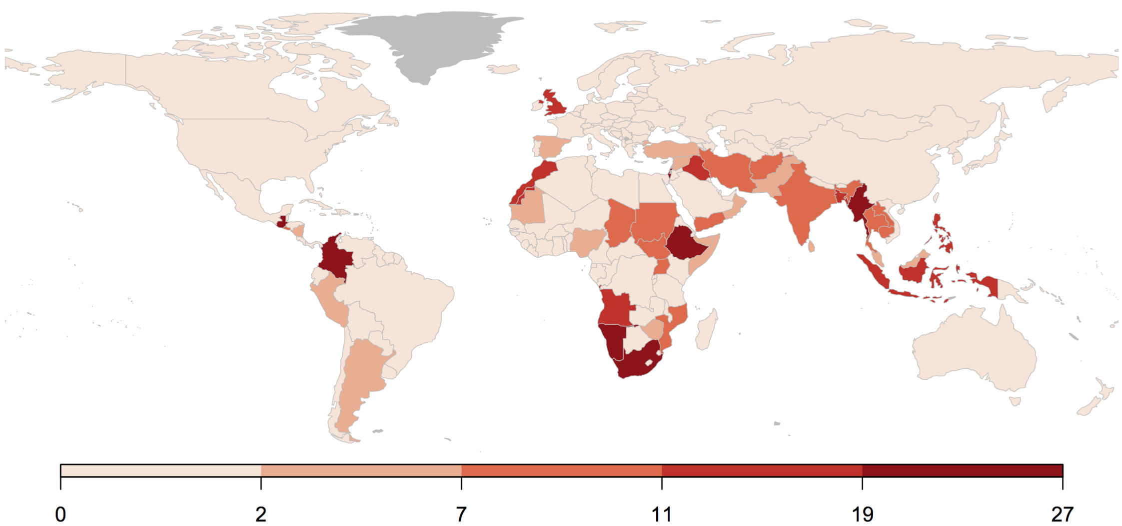
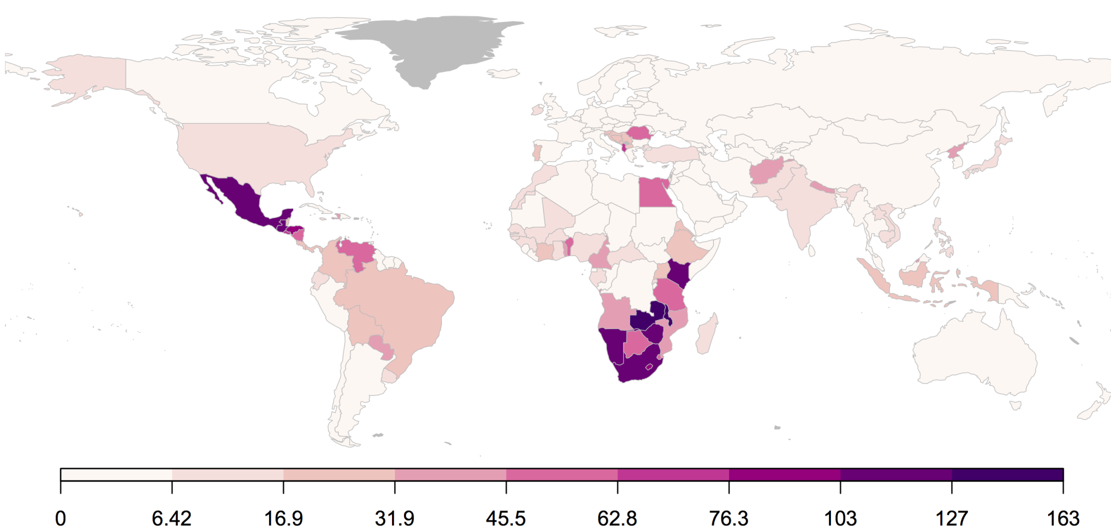


Figure 4.5: Maize, 1961 – 1988, KG per capita



The impact of food resources on rebellion is evaluated alongside other important confounders highlighted in the literature on internal conflict, socioeconomic development, and political institutions. First, it might be that food availability serves as a proxy for population-related consumption pressures such as the need to feed a large number of civilians and combatants (e.g., Fearon and Laitin, 2003). To account for these potential effects, I include two variables—*Population* and *Military personnel*—measuring the number of people living in a given country during a given year (in 1000s) (Gleditsch, 2002), and the number of people serving annually in each country's military forces (Singer, Bremer and Stucky, 1972), respectively.

Second, previous studies have highlighted the importance of economic development (as a measure of state capacity) or political openness on the likelihood and duration of rebellions (e.g., Fearon and Laitin, 2003; Collier and Hoeffler, 1998). To account for the possibility that the impact of food availability on conflict is driven by issues related to economic development or democratization, I include two general proxies for these potentially salient confounders. Economic development is captured by gross domestic product per capita, *GDP PC* coded by Gleditsch (2002). Democratization levels are coded based on the widely used Polity 2 measure, which ranges from -10 (most autocratic) to 10 (most democratic) (Marshall, Jaggers and Gurr, 2013). This variable, *Democracy*, was coded as one if a country received a score of seven or more on the Polity 2 indicator (i.e., a democracy), zero otherwise, in a manner used in past research (e.g., Fearon and Laitin, 2003).

Finally, as I argued in Chapters 1 and 2, the effect of food availability on rebellion might be the result of a lack of logistic support provided to the warring troops. To account for these possibilities, I include an additional indicator, *Military expenditure*, which codes the total expenditure (in USD) spent on the military in a given country during a given year (Singer, Bremer and Stucky, 1972). As such, whereas the variable *Military personnel* accounts for the *demand* aspect of food resources, this variable is a proxy for the amount of logistic support available to feed troops, at least among state forces, and hence for *supply* levels. I chose to include these theoretically-motivated variables in my models based on the recommendations of research on the statistical analysis of observational data, which recommends including only a small number of additional independent variables due to the potential biases that might arise from including a large number of potential confounders (Schrodt, 2014). Nevertheless, I illustrate the robustness of my findings to this empirical choice by reporting models that include a large number of additional controls in Table 4.6 in the next section. Summary statistics of all the variables used in this country level analysis (including those used in robustness models) are reported Table 4.4.

Table 4.4: Summary Statistics of Country Level Variables, 1961–1988

	Minimum	Median	Mean	Max	SD
Cross Sectional Analysis					
Rebellion	0	0	0.149	1	0.356
Maize (KgPC)[1]	0	1.710	1.881	5.184	1.543
Population[1]	4.701	8.812	8.767	13.902	1.670
Military personnel[1]	0	10.434	10.003	15.3744	2.899
GDP PC[1]	5.731	8.094	8.186	13.357	1.166
Democracy	0	0	0.261	1	0.440
Military expenditure[1]	0	18.698	18.256	26.485	4.126
$Rebellion_{t-1}$	0	0	0.147	1	0.354
Oil prod.[1]	0	0	6.859	20.239	7.700
Gas prod.[1]	0	0	1.259	8.539	1.967
Eth. frac.	0.001	0.349	0.399	0.925	0.290
Rel. frac.	0	0.374	0.374	0.783	0.220
% Mountains	0	9	17.574	94.3	21.200
Iron & steel[1]	0	0	5.963	18.909	7.146
Clim. disasters	0	0	0.124	3	0.365
Fats from cereals (daily grams)	0	4.130	4.904	17.340	3.472
Country area[1]	5.707	12.459	12.172	16.707	2.034
$Coup_{t-1}$	0	0	0.063	1	0.242
$Civil\ dis._{t-1}$	0	0	0.018	1	0.134
$Mass\ killing_{t-1}$	0	0	0.227	1	0.419
Intense rebellion	0	0	0.053	1	0.224
Over govt.	0	0	0.074	1	0.262
Hyd. disasters	0	0	0.263	10	0.714
Bio. disasters	0	0	0.064	5	0.314
Met. disasters	0	0	0.232	18	0.873
Geo. disasters	0	0	0.106	8	0.424
Natural disasters	0	0	0.790	22	1.680
Survival Analysis					
Rebellion termination	0	0	0.268	1	0.443
Rebellion duration	1	3	5.829	28	5.965
Maize (KgPC)[1]	0	2.180	2.088	5.156	1.553
Population[1]	4.701	9.414	9.386	13.638	1.494
Military personnel[1]	0	11.002	10.577	14.914	2.581
GDP PC[1]	5.731	7.745	7.785	12.974	1.028
Democracy	0	0	0.217	1	0.413
Military expenditure[1]	0	18.980	18.549	24.591	3.836

[1] Natural log

Because my first dependent variable is binary, I rely on logistic regression (i.e. logit) models for statistically assessing my first hypothesis. To control for time dependencies unaccounted for by the independent variables, all models include yearly dummies (i.e., year fixed effects). Because the data for some variables are duplicated over time, standard errors for all models are clustered by country. Fixed effects by country were not used for both theoretical—rebel groups frequently move between different countries (e.g., the Lord Resistance Army operating in Uganda, Sudan, South Sudan, and the DRC)—and practical—the coefficients on all independent variables in the fixed effects models where highly significant, suggesting estimation bias—reasons. Nevertheless, I do account for country-specific factors in several models that include random effects by country in Table 4.7 below. While endogeneity is less likely to affect the data because the FAO measures variations in maize production annually even in rebellion-afflicted countries (FAO, 2016), I take additional measures to account for this issue. To this end, I identify and estimate models that rely on the annual number of different types of natural disasters to instrument the effect of food production on rebellion in Table 4.8 below.

To evaluate my second hypothesis, I rely on the Cox proportional hazard model (Box-Steffensmeier and Jones, 2004). This model has the advantage of not imposing a functional form on the hazard parameter. A positive coefficient sign in this model means that the effect of this variable on the hazard of termination makes rebellion termination *more* likely. Note that the country year framework is likely to involve tied events—i.e., terminations occurring in the same value of t—while the Cox model assumes a continuous time-line. Although this problem is likely to bias coefficient estimates toward zero (i.e., toward insignificance) rather than the other way around, the Breslow method was used to handle ties.[18]

Results

The first three models in Table 4.5 report the results of three specifications used to evaluated the probability of the first phenomenon of interest, rebellion occurrence. The Baseline specifications include only the annual maize availability per capita indicator alongside year fixed effects. These Baseline specifications are followed

[18]Results remain robust when the Efron and exact methods are used for handling tied events.

by comparable models that include key controls for food consumption, *Population* and *Military personnel*, to arrive at a set of Full specifications that includes all the control variables discussed above. Across all models, *Maize (KgPC)* has a statistically significant and *positive* effect on rebellion occurrence during the 1961-1988 period, which lends strong support to hypothesis H1. Additionally, *GDP PC* is negative and significant and *Military personnel* is positive and significant, which follows theoretical expectations (e.g., Fearon and Laitin, 2003), while *Military expenditure* and, unexpectedly, *Democracy* are positive and significant (to at least the $p < 0.1$ level).[19] Substantively, as Figure 4.6 shows, a change across the entire range of *Maize (KgPC)* translates to a first difference change in the probability of rebellion of approximately 15% (in the Baseline model) to 5% (in the Full model), when all other variables are held at their median (for ordinal variables), or mean (for continuous variables) based on 1,000 simulations. These findings thus suggest that, as illustrated by the analysis of the Mau Mau campaign, rebellion patterns closely follow food abundance, even as one moves to the macrolevel.

For the second stage of analysis, which examines the impact of maize on rebellion duration, the next three models in Table 4.5 report a set of Cox proportional hazard models estimated only on countries and years that experienced ongoing rebellions. Again, the Baseline specification include only *Maize (KgPC)* and fixed effects by year, and additional controls are then added to arrive at the Full specification. All results support the hypothesized effect of staple crop availability on rebellion duration. Across all models, higher levels of *Maize (KgPC)* significantly

[19]The positive coefficient on *Democracy* is likely the result of "the lengthy (if generally low-intensity) conflicts in the United Kingdom, India, and Israel [that] demonstrate the general reluctance among democratic regimes to apply massive military force to quell peripheral separatist insurgencies" (Buhaug, Gates and Lujala, 2009, 563).

decrease the hazard of rebellion termination, i.e., making peace *less* likely. This lends additional supports to the argument developed above—which emphasize the relationship between (highly nutritional, durable, and easily transferable) food resources and the length of rebellions—and confirms Hypothesis H2. Moreover, the effect of food availability per capita is substantial. As the Kaplan-Meier plots presented in Figure 4.7 illustrate, a change in each maize indicator from its 25th to its 75th percentile (when all other variables are held at their means) decreases rebellion termination rates by $\sim 12\%$ in the 1961-1988 sample. In comparison, GDP per capita, a widely used indicator of conflict, has almost no observable effect on rebellion termination rates. These findings again suggest that higher availability of food resources prolongs rebellions by increasing rebel groups' fighting effectiveness and by motivating rebel troops.

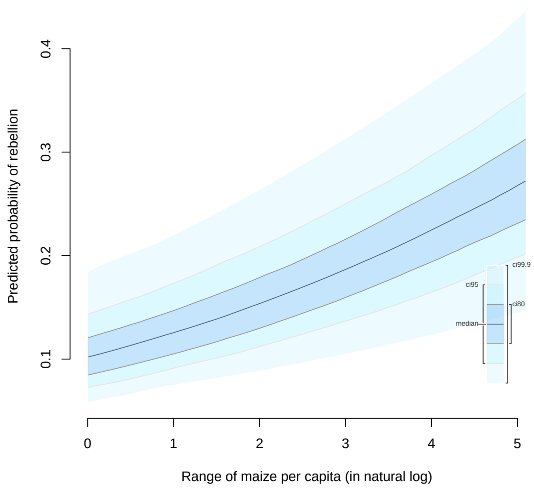
Despite the conscious effort done here to ensure empirical comparability between the micro- and macrolevel analyses and across cases in terms of both the temporal context and the explanatory variable of interest, I illustrates the theory's robustness and highlight its generalizablity to other contexts and crops using a large number of sensitivity analyses. These models, reported in the next section, account for numerous alternative confounders, modeling choices, and country-specific factors. Additional sensitivity models illustrate that the theory's viability in respect to contemporary rebellions (1961-2011) and cereals other then maize cannot be immediately rejected. Crucially, the effect of food availability remains statistically significant across all these different robustness analyses.

Table 4.5: Determinants of Rebellions, 1961-1988

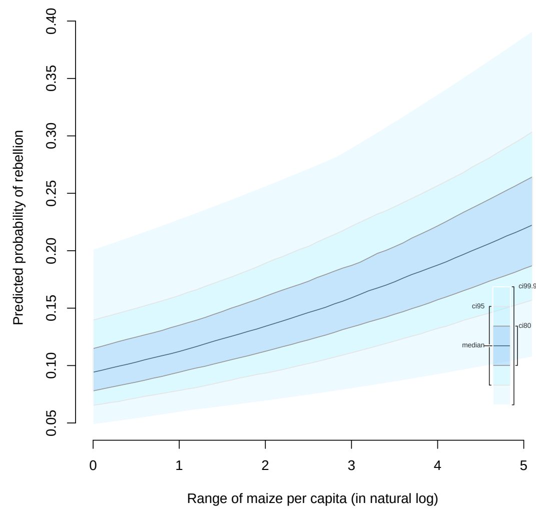
	Probability			Duration		
	Baseline	**Medium**	**Full**	**Baseline**	**Medium**	**Full**
Maize (KgPC)[1]	0.233***	0.196***	0.116***	−0.171***	−0.122***	−0.116***
	(0.030)	(0.033)	(0.036)	(0.046)	(0.045)	(0.047)
Population[1]	–	0.290***	0.020	–	−0.230***	−0.162**
		(0.051)	(0.066)		(0.066)	(0.078)
Military personnel[1]	–	0.074**	0.120**	–	−0.137***	−0.106***
		(0.037)	(0.061)		(0.027)	(0.035)
GDP PC[1]	–	–	−0.721***	–	–	0.023
			(0.083)			(0.067)
Democracy	–	–	0.604***	–	–	0.042
			(0.150)			(0.182)
Military expenditure[1]	–	–	0.182***	–	–	−0.048***
			(0.058)			(0.021)
Constant	−3.706***	−6.908***	−2.349***	–	–	–
	(0.340)	(0.445)	(0.675)			
Observations	3,931	3,908	3,639	801	796	750
Log Likelihood	−1,551.789	−1,459.163	−1,346.053	−1,381.388	−1,301.603	−1,199.558
Akaike Inf. Crit.	3,163.578	2,982.326	2,762.105	2,764.777	2,609.206	2,411.117

* indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$.
Variable coefficients are reported with standard errors clustered by country in parentheses.
Fixed effects by year included, although not reported here
[1] Natural log

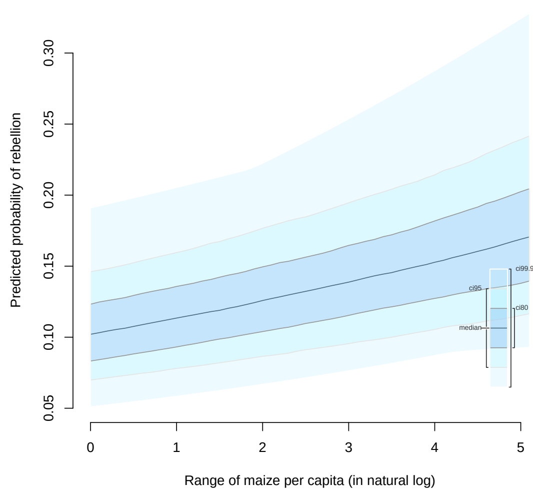
Figure 4.6: Percentage Change in the Annual Expected Probability of Rebellion – Maize (Kg per capita)



Baseline Model

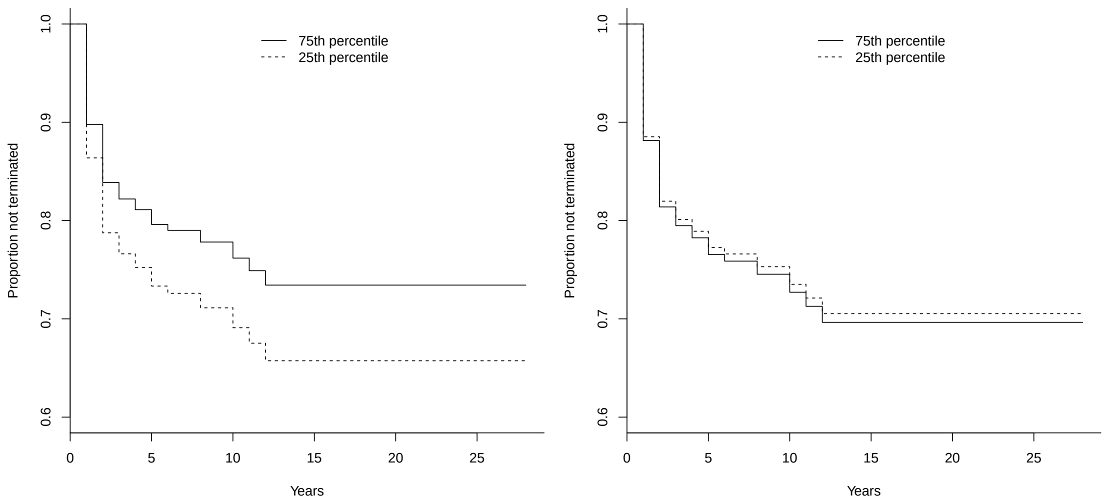


Medium Model



Full Model

Figure 4.7: Kaplan-Meier Curves of Cox PH Models – Full Model



Maize (Kg per capita) GDP per capita

Sensitivity Analyses

To evaluate the sensitivity of my findings, Tables 4.6 and 4.7 reports 12 robustness models that account for alternative confounders, specifications, and modeling choices. Each model relates to the Full logit specifications reported above. I begin by controlling for important alternative explanations, such as the one-year-lag of the dependent variable, and oil and gas production—obtained from Ross (2004*b*)—to account for the persistence of conflict and the role of other profitable natural resources in Model 1 in Table 4.6. Model 2 then additionally incorporates controls for ethnic and religious fractionalization and the percent of mountainous areas in a given country (obtained from Fearon and Laitin, 2003); iron and steel production to account for industrial capacity (obtained from Singer, Bremer and Stucky, 1972); and large-scale climatic disasters such as droughts and wildfires (obtaine from Guha-Sapir, Below and Hoyois, 2015), which can impact both food production and conflict (Miguel, Satyanath and Sergenti, 2004; Burke et al., 2009).

Next, recall that the theory developed in Chapter 1 and the microlevel evidence presented above associate rebellion incidence and duration with the efficiency that rebels can extract from available food resources, i.e., crops that provide that highest level of "fuel" to the warring troops. Therefore, to account for the role not only of maize, but of all other cereals in increasing the probability of rebellion, Model 3 replaces my maize-based indicator with a more comprehensive variable measuring the daily caloric intake from cereal-based fats for all cereal crops, including maize, rice, wheat, and others. This model thus captures the specific effect of grains in countries where the population is more dependent on cereals for its daily energy consumption, and hence in which—as the theoretical argument developed above suggests—the marginal gains for the rebels from securing access to food are the greatest. Model 4 re-estimates the Full logit specification over the entire temporal period for which data on all variables were available (1961-2011) to illustrate that the main analysis' findings are not unique to the 1961-1988 period. Because the effect of food resources might be important only in large countries—where the necessity to live off the land is greater—Model 5 replicated the Full specification with the addition of a variable measuring each country's land area (in square kilometers). Model 6 then replicates the Full specification while accounting for historical political violence events, such as coups d'état (obtained from Powell and Thyne, 2011), nonviolent civil disobedience (obtained from Chenoweth and Lewis, 2013), and state-led mass killing (obtained from Ulfelder and Valentino, 2008).

Moving to Table 4.7, because the significant coefficient on my maize availability indicator might be the result of the relatively low casualty threshold chosen to empirically define rebellions (25 or more combatant casualties), Model 7 replicates the Full specification, where the dependent variable is now operationalized as the annual incidence of a campaign involving 1,000 or more casualties (coded zero otherwise). Another alternative conceptualization of the dependent variable, where only rebellions fought specifically over the state's government and its institutions is used in Model 8. This model thus accounts for the possibility that rebel groups fighting such rebellions might be less dependent on locally sourced food, compared with rebels that fight to secure or secede a given territory. Next, recall that, as was mentioned above, fixed effects by country were not used, for both theoretical and practical reasons. Nevertheless, to account for country-specific random effects not captured by any of the variables in my model, which might influence rebellion propensity, Model 9 then re-estimates the Full model with the addition of random effects at the country level.

Next, to verify that the results are not driven by the reliance on logit regressions, Models 10 and 11 estimate a probit regression corresponding to the Full specification, in both regular (Model 10) and random effects (Model 11) frameworks. Last, considering that my sample contains relatively few observed instances of rebellion ($\sim$ 15.2% of the country-years in my 1961-1988 sample), Model 12 replicate the Full specification using a rare effects logit, which is more suited to handle such situations (King and Zeng, 2001). Crucially, the effect of food production per capita on rebellion remains significant (to at least a $p < 0.1$ level) across all these alternative models, suggesting that the empirical conclusions derived in this article cannot be immediately rejected.

Table 4.6: Determinants of Rebellions – Sensitivity Analyses

	(1) Ctrls.	(2) Ext. ctrls.	(3) Cereal nutrition	(4) 1961–2011	(5) Area	(6) Violence
Maize (KgPC)[1]	0.107*	0.111*	–	0.047*	0.102***	0.073*
	(0.063)	(0.066)		(0.025)	(0.036)	(0.038)
Nutritious cereals	–	–	0.065***	–	–	–
			(0.015)			
Population[1]	0.054	−0.009	0.041	0.099**	−0.067	0.025
	(0.123)	(0.140)	(0.064)	(0.047)	(0.071)	(0.071)
Military personnel[1]	0.024	0.070	0.123**	0.277***	0.164**	−0.027
	(0.103)	(0.124)	(0.060)	(0.048)	(0.064)	(0.062)
GDP PC[1]	−0.412***	−0.299*	−0.688***	−0.644***	−0.677***	−0.436***
	(0.145)	(0.156)	(0.082)	(0.055)	(0.083)	(0.092)
Democracy	0.315	0.486*	0.658***	−0.045	0.617***	0.940***
	(0.255)	(0.264)	(0.151)	(0.098)	(0.151)	(0.164)
Military expenditure[1]	0.214**	0.345***	0.160***	0.087**	0.165***	0.224***
	(0.091)	(0.117)	(0.055)	(0.042)	(0.058)	(0.064)
$Rebellion_{t-1}$	5.212***	5.086***	–	–	–	–
	(0.190)	(0.192)				
Oil prod.[1]	0.027	0.024	–	–	–	–
	(0.018)	(0.018)				
Gas prod.[1]	−0.201***	−0.212***	–	–	–	–
	(0.076)	(0.077)				
Eth. frac.	–	1.048***	–	–	–	–
		(0.390)				
Rel. frac.	–	−0.881*	–	–	–	–
		(0.465)				
% Mountains	–	0.005	–	–	–	–
		(0.005)				
Iron & steel[1]	–	−0.053**	–	–	–	–
		(0.023)				
Clim. disasters	–	0.363*	–	–	–	–
		(0.214)				
Country area[1]	–	–	–	–	0.105***	–
					(0.038)	
$Coup_{t-1}$	–	–	–	–	–	0.637***
						(0.199)
$Civil\ dis._{t-1}$	–	–	–	–	–	−0.008
						(0.344)
$Mass\ killing_{t-1}$	–	–	–	–	–	2.054***
						(0.122)
Constant	−5.240***	−8.084***	−2.510***	−3.179***	−3.320***	−4.652***
	(1.404)	(1.787)	(0.673)	(0.495)	(0.727)	(0.760)
Observations	3,473	3,390	3,639	7,056	3,442	3,605
Log Likelihood	−537.956	−527.136	−1,341.853	−2,649.100	−1,310.854	−1,179.513
Akaike Inf. Crit.	1,151.912	1,140.272	2,753.706	5,414.200	2,693.707	2,435.025

* indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$

Variable coefficients are reported with standard errors clustered by country in parentheses

Fixed effects by year included, although not reported here

[1] Natural log

Table 4.7: Determinants of Rebellions – Sensitivity Analyses (Continued)

	(7) Intense	(8) Over govt.	(9) RE	(10) Probit	(11) RE probit	(12) Rare events
Maize (KgPC)[1]	0.121**	0.137***	0.309*	0.072***	0.176*	0.114***
	(0.056)	(0.047)	(0.165)	(0.020)	(0.093)	(0.036)
Population[1]	−0.457***	−0.288***	0.034	0.025	0.043	0.023
	(0.101)	(0.089)	(0.276)	(0.037)	(0.155)	(0.066)
Military personnel[1]	0.279***	0.184**	−0.0002	0.068**	−0.006	0.116*
	(0.107)	(0.084)	(0.115)	(0.032)	(0.064)	(0.061)
GDP PC[1]	−1.397***	−0.940***	−0.977***	−0.380***	−0.533***	-0.708***
	(0.137)	(0.108)	(0.256)	(0.046)	(0.139)	(0.0823)
Democracy	0.114	0.369*	0.458	0.299***	0.160	0.594***
	(0.302)	(0.218)	(0.301)	(0.082)	(0.164)	(0.150)
Military expenditure[1]	0.335***	0.138*	0.605***	0.095***	0.318***	0.179***
	(0.100)	(0.072)	(0.098)	(0.031)	(0.053)	(0.058)
Constant	1.461	2.809***	−10.840***	−1.547***	−6.093***	-2.302***
	(1.075)	(0.927)	(2.930)	(0.371)	(1.659)	(0.675)
Observations	3,639	3,639	3,639	3,639	3,639	3,639
Log Likelihood	−596.400	−852.153	−778.437	−1,344.084	−784.926	−1346.050
Akaike Inf. Crit.	1,262.800	1,774.305	1,576.875	2,758.168	1,589.852	2,762.100

* indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$

Variable coefficients are reported with standard errors clustered by country in parentheses

Fixed effects by year included, although not reported here

[1] Natural log

Instrumental Variable Regression

As was mentioned above, in this section I take additional measures to account for the potentially simultaneous relationship between food production and rebellions. Specifically, I re-estimate the Full specification using a two-step probit model (Rivers and Vuong, 1988). This two-step approach illustrates the probability of the dependent variable being one given the values of the regressors in the absence of endogeneity, which makes it possible to trace the effects of changes in the (potentially endogenous) food production variable on the probability of rebellion. Each of these analyses relies on a different, theoretically-motivated instrument, such that the Full specification analysis is repeated six times, once for each instrument category. These models reasonably isolate the direct effect flowing from food production to rebellions rather than the other way around, and show that the main analysis' findings are unlikely the result of simultaneous relationships between the two variables, thus providing additional confirmation to the linkages between higher food availability and rebellion incidence and duration at the country level.

To this end, this section first describes my identification strategy and methodology, then reports the results of six two-step probit models replicating the Full specification from the main dissertation, once for each instrument. This approach builds on the work of Rivers and Vuong (1988)[20] to illustrate the probability of the dependent variable being one given the values of the regressors, in the absence of endogeneity, which means that it makes it possible to trace the effects of changes in the (potentially endogenous) food production variable on the probability of rebellion. These models reasonably isolate the direct effect flowing from food production to rebellions rather than the other way around, and to show that the findings are unlikely the result of simultaneous relationships between the two, thus providing additional confirmation to the linkages between food abundance and rebellion developed in this chapter.

Identification and Methodology

The impact of maize resources on rebellion and its duration is evaluated in two stages. First, note that just as maize production might influence rebellion occurrence, it is possible the latter might impact maize production by destroying infrastructure, disrupting migratory labor and remittance patterns, and even causing famines (Messer, 2009). To verify the robustness of my findings to these concerns, the identification strategy used in this section to evaluate the impact of maize

[20]See also, Blundell and Powell (2004).

production on *Rebellion* relies on the use of an instrumental variable (IV), i.e., a variable that is correlated with food prices but arguably uncorrelated with the error term of *Rebellion*. Recall that such an IV must satisfy two requirements. First, it must be correlated with food production at the country level. This is easily ascertained with statistical tests—in effect, tests of the null hypothesis that the instrument is weak—the results of which are shown in Table 4.8 below. Second, it must only affect rebellions through food production, a requirement that is also known as meeting the exclusion restriction (Angrist and Pischke, 2009, 87-89). Because empirically testing this latter assumption is challenging, especially in non-linear IV models such as the two-step probit, it is worth discussing its validity in this context in more detail.

The variable used to identify the causal relationship between maize production and rebellions is the number of natural disasters—all droughts, earthquakes, epidemics, episodes of extreme temperature, floods, insect infestations, mass movements (both dry and wet), storms, volcanic eruptions, and wildfires—in a given year, coded by the Center for Research on the Epidemiology of Disasters (CRED) (Guha-Sapir, Below and Hoyois, 2015). This approach builds on previous research that uses the same disaster to instrument the effect of food prices on urban unrest (Bellemare, 2015) or civil war (Miguel, Satyanath and Sergenti, 2004). That such natural disasters constitute shock to the supply and demand of food should be relatively uncontroversial, and have hence been used in previous research (e.g., Bellemare, 2015). These natural shocks can also all depress economic growth, which leads to reduced incomes and thus to a decreased demand for food. Nevertheless, to illustrate that the findings are not driven by one particular disaster type, and because some disasters—such as climatic events—might affect violence via pathways other than impacting food compared with others—e.g., biological events—where the exclusion restrictions is much more likely to hold, I conduct a set of analyses that rely on each disaster type separately to instrument food production.

To identify the relationship between natural disasters, food production, and rebellions, I rely on the two-step approach developed by Rivers and Vuong (1988). Whereas linear approaches are disadvantaged in that they may imply probabilities outside the unit interval, generalized linear models, like probit or logit, are used to model binary dependent variables in applied research, which allowed Rivers and Vuong (1988) to extend the probit model to account for endogeneity.[21] Thus, in the first stage, the researcher regresses the instrument and controls on the endogenous regressor. The resulting residuals (standardized by their standard deviation, a necessary step in the two-step probit approach) are then included as an additional regressor instead of the endogenous variable in the second step when the probit model of interest is estimated. Building on this approach the identifying assumption is thus that natural disasters, both aggregated and by type, are uncorrelated with ϵ_{1it} in equation

$$Pr(y_{it} = 1) = \Phi(\alpha_1 + \beta_{1f}\hat{f}_{it} + \beta_{1X}X_{it} + \phi_{1t}t_t + \epsilon_{1it}) \tag{4.1}$$

where Φ is the probit function, and $\hat{f}_{it}$ are the predicted values of f_{it}, i.e., maize availability per capita, obtained from the first-stage regression of maize production on climatic disasters and all the control variables X in equation 4.1, such that

[21] The results remain robust when regular 2SLS models are used.

$$f_{it} = \alpha_2 + \beta_{2c} c_{it} + \beta_{2X} X_{it} + \phi_{2t} t_t + \nu_{2it} \tag{4.2}$$

where c_{it} is the annual (t) number of natural disasters in country i; ν_{2it} is an error term with mean zero; X_{it} is a matrix of the annual impact of all controls in a given country i; and t_t are the fixed effects by year. If the instrument is valid and effectively "exogenizes" maize production relative to rebellions, the coefficient β_{1f} is the local average treatment effects (LATE) of maize production on rebellion, i.e., the increase in the extent of global rebellions (as measured by the dependent variable) due to maize production in those years and countries where natural disasters induce a change in maize production (Angrist and Pischke, 2009, 110-111).

How are natural disasters a good IV for food availability per capita in the context of Equations 4.1 and 4.2? Within a given year, natural disasters constitute unpredictable shocks to both the supply of and demand for food.[22] Although the use of rainfall as an IV has recently been questioned due to the predictable nature of rainfall (see discussion in Sovey and Green, 2011; Sarsons, 2015), the natural disasters used in this IV analysis are unpredictable. Indeed, although some of the natural disasters are certainly more likely in certain seasons (e.g., floods in winter, droughts in summer), the presence of yearly and dummies in Equations 4.1 and 4.2 eliminates the impact of annual natural trends by controlling for annual predictability. In other words, while it is true that floods are likely on an annual

[22]Although natural disasters are usually conceived of as shocks to the supply of food (Bellemare, 2015; Miguel, Satyanath and Sergenti, 2004), the fact that natural disasters can kill or displace large numbers of people makes them equally, if not more likely to also affect the demand for food. Because there are many more consumers of food than producers, exposure to natural disasters should affect consumers of food disproportionately more than they affect producers.

basis, and thus a priori (somewhat) predictable in a given year, the impact of variations away from this trend should be unpredictable once the time trend is controlled for. Similarly, the inclusion of year fixed effects should control for linear increases in the number of rebellions, maize production, and the number of natural disasters due to the passage of time.

Natural disasters could also lead to job losses via destroyed capital, which would make it easier to recruit disaffected and disenfranchised populations as combatants in rebellions. Once again, this possibility is unlikely to compromises the empirical results. Indeed, for this to happen, a natural disaster must directly lead to a full-scale rebellion within the same country in which it takes place (e.g., an earth quake leads to years of bloody civil war throughout the entire world region), which would in turn require that devastation levels are so high that they overcome the effect of food production across this and other countries. This is not impossible, but it is highly unlikely given the scope of the data; the fact that as the data show variations in maize yields, even in bad years, tend to be relatively low; and the inclusion of a large number of countries, only in few of which maize is so susceptible to natural disasters as to be almost completely eliminated by the impact of a natural disaster during a given year. Moreover, recent research illustrates that, while they can serve as a trigger, natural disasters such as droughts are highly unlikely to directly generate such high levels of violence and do little to induce massive migrations as previously hypothesized (e.g., Selby et al., 2017), especially because the relationship between climate and conflict "appear to be scale- and context-dependent" (Hendrix, 2017). Finally, Equations 4.1 and 4.2 include income as a control variable, which additionally accounts for the impact of the level of purchasing power in respect to food on rebellion.

Two-Step Probit Analysis Results

Table 4.8 presents the second-stage probit estimates corresponding to the Full logit model specification from table 4.5. The first model uses the total amount of all natural disasters occurring within a given country during a given year, with each subsequent model using only one type of natural disasters according to their classification in the EM-Dat International Disaster Dataset (Guha-Sapir, Below and Hoyois, 2015). Thus, hydrological disasters include all events classified as floods, landslides, and wave actions. Biological disasters include all epidemics, insect infestations (e.g., locust), and other animal accidents. Meteorological disasters include extreme temperatures, fog, and storms. Climatological disasters are defined, as mentioned above, as all droughts, wildfires, and glacial lake outbursts. Finally, geophysical disasters include earthquakes, other mass movements, and volcanic activity.

As Table 4.8 illustrates, when "exogenized" in respect to rebellion, the coefficient of the instrumented maize availability per capita indicator $\widehat{Maize}$ $(KgPC)$ still produces a (highly) statistically significant effect on rebellion. This provides strong confirmation to the findings presented in Table 4.5 by showing that when the causal arrow flows from food toward rebellion rather than the other way around, the main analysis results remain significant and observable. It is important to stress that while Stock and Yogo (2002) recommend an F-statistic threshold of 10 or more for a variable to be considered not weak, no one (to the author's knowledge) have so far attempted to extend the same analysis to two-stage probit analysis. Nevertheless, Table 4.8 clearly shows that in at least one case (geophysical disasters), the weak instrument F-statistic exceed the threshold of 10 recommended by Stock and Yogo (2002). Thus, the statistical findings presented below and the theoretical justification for the particular instruments used for analysis show that the relationship between food abundance and rebellion is *not* the result of the simultaneous relationship between the two phenomena. Rather, higher levels of food availability per capita impact the probability of rebellion occurrence, which is in line with both the theoretical argument of the main dissertation, and the micro- and macrolevel empirical analyses results reported therein.

Table 4.8: Determinants of Rebellions, IV Probit Results – Second Stage

	All	**Hydrological**	**Biological**	**Meteorological**	**Climatological**	**Geophysical**
$\widehat{Maize}\ (KgPC)^1$	0.094***	0.095***	0.099***	0.097***	0.099***	0.093***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Population[1]	0.050	0.050	0.049	0.050	0.049	0.050
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Military personnel[1]	0.061*	0.061*	0.061*	0.061*	0.061*	0.061*
	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)
GDP PC[1]	−0.403***	−0.403***	−0.404***	−0.404***	−0.404***	−0.403***
	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)
Democracy	0.276***	0.276***	0.275***	0.275***	0.275***	0.275***
	(0.081)	(0.081)	(0.081)	(0.081)	(0.081)	(0.081)
Military expenditure[1]	0.090***	0.090***	0.091***	0.090***	0.091***	0.090***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Constant	−1.227***	−1.227***	−1.227***	−1.227***	−1.226***	−1.229***
	(0.359)	(0.359)	(0.359)	(0.359)	(0.359)	(0.359)
Observations	3,639	3,639	3,639	3,639	3,639	3,639
Log Likelihood	−1,344.602	−1,344.434	−1,343.907	−1,344.143	−1,343.960	−1,344.731
Akaike Inf. Crit.	2,759.203	2,758.867	2,757.813	2,758.285	2,757.920	2,759.462
Weak-instrument	3.658	3.057	1.332	0.824	0.228	11.910

* indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$

Variable coefficients are reported with standard errors clustered by country in parentheses

Fixed effects by year included, although not reported here

[1] Natural log

Selection Issues

It is important to recognize that a selection problem might arise if access to food resources influences a group's decision whether or not to embark upon a rebellion. However, I believe that this issue does not adversely affect the theoretical, and consequentially empirical approach advocated here. First, the claim that countries where more food per capita is available are more likely to experience rebellions because rebel groups "choose" to be formed there is in-line with the argument that the probability of rebellion varies according to food availability, because it suggests that food in not a constant factor across countries. Rebel groups operating in countries with more food "select" to be formed in these states because they know that higher local food availability means they can access it more easily, which gives them an advantage in the probability of fighting longer and eventually winning.

Second, the argument presented in the dissertation asserts that it is the *continuous* access to resources that influences the fighting capability of groups, such that rebel organizations with more access to food resources can, on average, fight harder and longer. This in contrast to the binary perspective on these issues, according to which having *any* access to food influences fighting capacity, regardless of how much food is available.

Third, considering that rebellions are dynamic processes, groups can "update" their level of food access throughout the campaign, which means that even in countries where groups selected to form and start a campaign, if annual food availability levels drop during a given year, or if the group loses access to areas with nutritious food resources during the fighting, then its size and fighting ability will correspondingly decline. This is because food support varies not only across countries, but also over time.

Finally, the focus on ongoing rebellions as part of my empirical strategy helps to verify that this selection problem does not effect the main empirical findings, as groups already engaged in rebellions have managed to secure at least some adequate access to food. Thus, even if selection problems are responsible for the results observed in the rebellion probability stages (i.e., logit models), it cannot explain the findings observed in the duration stage.

Conclusion

In this chapter, I provided an empirical verification of the final part of the theoretical framework developed in Chapter 1 to show that—more than being a generator of conflict locally—food resources shape the occurrence and outcome of large scale rebellions. The Mau Mau rebellion remains the canonical example of a large-scale conflict in a developing country where food resources were crucial in shaping conflict patterns and their outcome. This was recognized by the British colonial occupiers, who sought to defeat the Mau Mau by draining their food support. Having provided archival qualitative evidence to show the importance British officials attribute to controlling food resources and reducing their accessibility, I proceeded to analyze to microlevel datasets compiled using these archival evidence. I found that, as expected according to the qualitative archival evidence, Mau Mau rebels moved into districts where more food is grown to obtain food resources for self sustenance. I then tested the applicability of this microlevel evidence to a other rebellions occurring globally, to show using different methodological approaches that food resources have also had a strong effect on rebellion occurrence and duration globally during the Cold War period.

The findings presented in this chapter strongly suggest that scholars should better account for the role of food resources in contemporary analyses of conflict. From a theoretical perspective, conflict and rebellions in developing countries are likely to involve strong food security-related incentives, as both rebels and—frequently—state forces are forced to rely on locally sourced food (Koren and Bagozzi, 2016). In such low development contexts, the marginal returns from more food available per capita are sizable. Moreover, unlike other profitable natural resources, food is absolutely necessary for rebellions to succeed. These incentives are thus likely to shape the behavior of armed troops even more than elements such as state capacity economic development, and should thus be better incorporated into extent frameworks of conflict analysis.

From an empirical perspective, the effect of food resources on rebellion is shown not only to be statistically significant, but also sizable, and substantively comparable to that of other benchmark indicators of conflict such as GDP per capita (Fearon and Laitin, 2003; Ward, Greenhill and Bakke, 2010). As such, scholars of conflict and political violence more broadly should include food resources-based indicators in models analyzing conflict occurrence and duration as to verify the robustness of their findings to these issues. The strong role of food resources is not related to economic development, although, as mentioned above, these factors likely play a much greater role in lower development contexts, state capacity, or political openness. Their viability as an alternative mechanism generating conflict should thus be taken into consideration.

Conclusion: Food Insecurity and Violence in the Developing World

Summary of Findings

Research on civil war treats food support as constant. The argument developed in this dissertation asserts that, as a crucial input for conflict, food security has a varying and substantial impact on its onset, conduct, and outcome. This dissertation laid out a multi-level theory to explain the role of regular access to locally-sourced nutritious food during conflict, emphasizing not only the physical importance of regular support, but also its psychological and sociological impact on troops' morale. Groups that have access to more nutritious food resources can improve their performance, increase internal cohesion, and fight harder and longer. These groups can also operate in larger contingents and embark on more complex operations, rather than being constrained to fighting only small, limited skirmishes. Access to more (nutritious) food resources also provides group leaders with the ability to credibly commit to their troops and illustrate that the group is resilient and durable. This gives group members, in turn, the motivation to fight and follow their leaders, and binds troops together to work toward a common goal.

Throughout the dissertation, I developed this argument in several stages. In

Chapter 1, I presented the broad framework connecting food abundance to more violence. I explained that exactly because it is important, current research on civil war, and political violence more broadly, tends to treat food support as constant. I defined the term "food security" as used throughout this dissertation and showed that food is a unique natural resources due to three particular characteristics. First, securing food resources is *compulsory*, meaning that groups cannot operate without food. Second, securing food resources is *agnostic*, because regardless of the motivations that lead a person to join an armed group, being fed regularly is a necessity that trumps all other impetuses for fighting. Finally, because it is compulsory and agnostic, having ample access to food resources also has *binding* features; nutritious, regular access to food brings troops closer together and provides leaders with credible commitment to illustrate they can fight longer conflicts.

I have also shown that the focus on the role of food security complements a large number of bodies-of-research on conflict and political violence more broadly. Indeed, understanding how food security affects dynamics of violence can inform current approaches that argue climate change has a strong impact on the civil war in developing countries (e.g., Burke et al., 2009; Miguel, Satyanath and Sergenti, 2004; Hsiang, Burke and Miguel, 2013). It also informs our understanding of how natural resources condition the probability and duration of conflict (e.g., Weinstein, 2005; Collier and Hoeffler, 1998), by showing that more than lucrative natural resources, the imperative to secure food is fundamental. It also provides a different perspective on how state capacity conditions the geospatial distribution of conflict (e.g., Fearon and Laitin, 2003; Koren and Sarbahi, Forthcoming; Buhaug, Gates and Lujala, 2009), by showing that the effect of food on global rebellions is at least comparable to that of other, heavily studied factors. Finally, I illustrated that incorporating the role of food more throughly into research on civilian victimization, specifically, can help explain where and when such tragic incidents are more or less likely to occur, which is in-line with a rapidly expanding body of research (e.g., Anderson, Johnson and Koyama, 2017; Koren and Bagozzi, 2017; Bagozzi, Koren and Mukherjee, 2017).

Considering that food impacts conflict through different mechanisms, the ensuing chapters developed some crucial pathways. In Chapter 2 I focused on one such pathway, arguably the most fundamental one, which I termed *possessive conflict* over food security. I discussed four armed group categories, each with its own specific motivations to initiate conflict over food resources in order to secure food for their own consumption. Briefly, official state forces and militias without regular support from the state would move into food abundant areas in order to secure food resources to support their operation in the region. Rebel groups might do the same, but they also frequently do so that they can trade these resources on the open market to generate revenues. Agriculturalist militias fight to defend their own property and to take control over food abundant areas to prepare for periods of scarcity. Pasturalist militias fight to obtain resources they cannot grow themselves due to their mobile lifestyle.

Considering that food resources might not only impact the frequency of conflict, but also be affected by it, the local staple crop yield indicators used to validate this argument were instrumented using drought intensity levels, which—as recent studies posited—can influence conflict through food production. The causal relationship between local food production and violent conflict is thus identified using this climatic variable (Miguel, Satyanath and Sergenti, 2004). It is important to stress that previous research has suggested that rainfall variations might be not be an ideal instrument of income shocks (Sarsons, 2015). Although the argument developed in Chapter 2 does not necessarily equate local yields with income, I nevertheless addressed this concern both theoretically—by discussing some distinctions of African agriculture systems—and empirically, by showing that my drought-based instrumental variable is at least "plausibly exogenous" (Conley, Hansen and Rossi, 2012).

The findings of the analyses conducted in Chapter 2 suggest that agricultural regions experience relatively high levels of violent conflict that are, to a large extent, driven by the type and amount of food resources produced there. These findings diverge from the current conceptualizations of this relationship in mainstream literature, which frequently attribute conflict to sudden food shortages (e.g., Burke et al., 2009; Maystadt and Ecker, 2014). Thus, Chapter 2 lends support to the theoretical argument developed in Chapter 1 by theorizing and showing that scarcity-based explanations are insufficient in explaining localized conflict over food resources, their potential validity notwithstanding.

In Chapter 3 I turned to examine the notion that a substantial portion of localized conflict events in food abundant areas arise over the need to control the amount of food resources available to rival groups. I thus developed the argument that reducing rival groups' access to food resources is a powerful strategy to increase strength and guarantee survival, as being deprived of food support significantly reduces an organization's fighting ability (Hendrix and Brinkman, 2013), a mechanism I termed "preemptive" conflict over food security. Because the majority of armed actors in the developing world must frequently rely on locally-grown food to support their operations, by securing access to such resources an armed actor can operate for longer periods of time and venture further away from its base of operations, increasing its durability. Correspondingly, to weaken its opponent and increase its probability of defeating its rivals, an armed group might seek to *preemptively* conquer areas that have more food resources. In doing so, it deprives the first group of these essential resources, thus reducing its durability, fighting capability, and size. This in turn will push the first group to stage stronger resistance in these food abundant areas to guarantee continued availability of food resources.

I then derived a formal model to show how food security concerns affect the strategic calculi of (i) the first group, or defense forces, (ii) the second group, or raiders, and (iii) the civilian producers that provide local food support to the defense forces. I then corroborate my formal model's predictions on high resolution data on conflict and local food production for the years 1998-2008 (Ray et al., 2012; Ramankutty et al., 2008) using a *statistical strategic* model that corresponds to the formal model's derivations, and also used this model to forecast conflict on out-of-sample data for 2009-2010. In discussing the preemptive imperative to initiate conflict in food abundant resources and validating it empirically, Chapter 3 thus advances our understanding of how localized conflict might emerge *endogenously* of the strategic choices of different groups, and sets the stage for evaluating how these two mechanisms—possessive and preemptive conflict over food—impact war and rebellion patterns at the macrolevel.

Having laid out and validated the two most important mechanisms linking food abundance to conflict locally, in Chapter 4, I conducted an empirical assessment of the argument developed in Chapter 1. Microlevel evaluation of archival documents from the Mau Mau rebellion in Kenya, backed by quantitative analyses of original within-country data on localized conflict during the rebellion, established this theory's viability, focusing on the possessive and preemptive conflict dynamics. Documents from deliberations of British officials during the rebellion illustrate that these officials were acutely aware of how important food resources—and especially nutritious, calorie-rich staple crops—were to the Mau Mau fighting efforts. Using an original geo-spatial dataset I constructed from additional archival documents, geographic patterns of violence during the Mau Mau rebellion are also tested *quantitatively* to evaluate these claims.

Having established the microlevel impact of food resources in this specific historical case, the second part of Chapter 4 evaluated whether the probability and duration of rebellions on a global scale is impacted by annual variations in nutritious food availability at the country level. I found that not only are rebellions significantly more likely to erupt in countries where more food is available, but also that—once erupted—rebellions are likely to last significantly and substantially longer. Indeed, the hazard of conflict termination (i.e., peace) in countries at the 75th percentile of maize production decreased by 12% compared with states in the 25th percentile. Considering that food resources might exhibit an endogenous relationship with conflict, even at the country level, I also conducted a two-step probit regression with instrumental variables to show that the results are likely robust to such concerns. To do so, I relied on the annual frequency of natural disasters for each country, both disaggregated to specific categories, and at the aggregated level. In line with the theoretical expectations developed in Chapter 1 and the findings of the microlevel analyses conducted in Chapters 2, 3, and the first part of Chapter 4, I found that in countries with higher levels of staple crop availability, rebellions are more likely to arise, and when they do, last longer.

The rest of this conclusion revolves around four themes. I first discuss this dissertation's theoretical and empirical contributions, especially in respect to the reliance on high-resolution data, which allow me to evaluate cross-nationally how violence varies within states. I then elaborate on the policy implications of my analysis. In the third section I discuss some of the limitations of my analysis. Finally, I discuss some potential extensions of this research, including future directions to pursue and how my findings relate to other bodies of research on conflict and political violence.

Theoretical and Empirical Contribution

My findings have a number of important implications for the study of conflict and political violence. Anecdotal narratives, historical analyses, and quantitative empirical evidence all suggest that in many (low development) contexts, food abundant areas attract a substantive degree of violence by both state and nonstate actors including rebels, especially during ongoing wars. In recent decades, our understanding of the causes of conflict has benefited from numerous studies into the importance of natural resources (e.g., Collier and Hoeffler, 2005; Weinstein, 2005; Azam and Hoeffler, 2002) and low state capacity (e.g., Fearon and Laitin, 2003), as well as research that emphasizes the strategic logic behind political violence (e.g., Valentino, Huth and Balch-Lindsay, 2004; Wood, 2010; Kalyvas, 2006; Fjelde and Hultman, 2014). Other research took a step forward by incorporating the notion that climatic variations (Burke et al., 2009; Miguel, Satyanath and Sergenti, 2004; Hsiang, Burke and Miguel, 2013) and food prices (Bellemare, 2015; Fjelde, 2015; Hendrix and Haggard, 2015; Weinberg and Bakker, 2015) impact the probability and frequencies of different social conflict.

Importantly, despite these impressive bodies of research, there are at least two important areas in the research on civil conflict and political violence where our understanding remains poor, as highlighted by Blattman and Miguel (2010). The first is in "analyzing conflict causes, conduct, and consequences at the level of armed groups, communities, and individuals" (Blattman and Miguel, 2010, 8). The second is the fact "the empirical evidence that social divisions, political grievances, and resource abundance are drivers of violence," currently "remains weaker and more controversial" (Blattman and Miguel, 2010, 45).

My main contributions to these impressive bodies of research are fourfold. First, I create a general theory and identify mechanisms that, while being focused on microlevel dynamics of violence, also has testable macrolevel implications. From a microlevel perspective, I argue that efforts to understand where conflict and civilian victimization arise and concentrate should take into consideration the importance of securing food resources, and the fact that in many countries forces must guarantee these resources by violent means. Here, my theory, mixed-methods case study, and analysis of high-resolution data explain how concerns at the group and individual troop level shape local conflict patterns, thus allowing me to more carefully conceptualize my macrolevel analyses and the factors tested therein. My archival-resources based dataset and the incorporation of high-resolution crop yield data—both of which are now available to other scholars—also contribute toward "a major goal of civil war researchers within both economics and political science," which "should be the collection of new data, especially extended panel micro-data sets of economic conditions and opportunities" (Blattman and Miguel, 2010, 46). Focusing on violent interactions between different groups occurring at the highly-localized level using a variety of tools, including game theory, yields a rigorous explanation for conflict and political violence more broadly.

Importantly, I am also able to test the viability of these microlevel findings across a large number of countries by focusing on the expected macrolevel outcome: violent conflict. Here, the reliance on a global 0.5 degree resolution grids provides a major advantage. My microlevel theory identifies specific contexts where food abundance can generate violence, and then extrapolates how these should affect interactions occurring at the macrolevel. Using my high-resolution grid data, I am able to test how this contextualized dynamic of violence compares with other areas within the state, urban or rural. I focus on the geographical manifestations of specific types of political violence, and how these relate to theoretical expectations. In doing so, I unpack how some specific features of low-development states that may vary over time and space, such as economic productivity and agricultural output, as well as factors that might hinder state access such as mountains and distance from centers of power, impact armed conflict and other human rights violation.

Second, by focusing on geospatial variations in violence I am also able to generalize my theory about the linkages between food abundance and conflict as well as its underlying mechanisms to contexts that do not involve an ongoing civil war. By viewing armed group behavior as a byproduct of the conditions of war, many studies on the causes of conflict and political violence provide relatively few insights into why these phenomena tend to concentrate in specific specific areas or erupt in moments. The focus on civil war, which is fought primarily in rural areas (Kalyvas, 2004), also means that these studies often ignore how specific features of such rural areas might attract significantly higher levels of violence even during times of peace.

A related insight is that in the vast majority of contexts, food is not grown by the rebels themselves, but by civilians within territories where rebels operates. This suggests that studying the behavior of civilians as an active actor in rebellion and the factors underlying their decision to provide food support to rebels or to state troops can yield important insights into pathways governing the spread of armed conflict. The decision whether or not to feed the rebels can blur the line between rebellion supporters and participants as highlighted by, e.g., Wood (2003, 17-18). Explicating the role of food as a builder of pro-rebel communities will likely generate important insights into the behaviors of civilian, rebels and state troops during rebellions, and is thus an especially salient future direction of research.

The finding that a large portion of this violence concentrates in areas with more food abundance, as was preliminarily shown in Table 1.1 in Chapter 1, has additional theoretical implications. It points to the fact that some types of social conflict, including civil war and rebellion, are highly context-dependent. For instance, by showing that conflict can also arise endogenously in areas where more food is grown I am able to explain how food abundance can *cause* conflict, while still relying on the strategic violence approach. This adds to "the empirical evidence that social divisions, political grievances, and resource abundance are drivers of violence," which currently "remains weaker and more controversial" (Blattman and Miguel, 2010, 45). Finally, as in detail below discussed below, these identified linkages can also assist policymakers to better direct their intervention efforts.

Third, while in this dissertation I focus on food as a unique natural resource, my theory and analysis can be readily expanded to incorporate other types of resources. For instance, gem stones such as diamonds are found in mines, but then could be placed in one's pocket and carried across the border, where they can be sold in their relatively raw form (although more processing can add value to the final produce). In that regard, these lucrative resources are probably more similar to nutritious food resources such as maize in that processing, while potentially beneficial, is not necessary. In contrast, oil is unlikely to be obtained, processed, and sold if the group is unable to establish control over the entire supply chain, i.e. the state apparatus back in the capital and far away from the fields (see, e.g., Englebert and Ron, 2004). The focus on issues of access and availability can thus inform the field's understanding of how different natural resources might have varying effects on the probability and concentration of conflict and violence.

Finally, this dissertation also has implications for scholars studying the effect of climatic variations, especially in respect to food availability and access, and social conflict. Recent research into the relationship between climatic variability and conflict identifies factors such as prolonged heat waves and droughts as potential causes of conflict and violence (Burke et al., 2009; Miguel, Satyanath and Sergenti, 2004; Bagozzi, Koren and Mukherjee, 2017; von Uexkull et al., 2016). However, some scholars rightfully highlight the potential pitfalls of placing too much responsibility for conflict and political violence, with all their complexities, on broad climatic trends (see, e.g., Buhaug, 2010). Thus, as I emphasize repeatedly throughout this dissertation, my findings illustrate that negative rainfall shocks and their associated effects are *not* uniform drivers of the risk of violence. Indeed, I echo the warning advanced by Buhaug et al. (2014) that making such brush-stroke argument can lead to problematic interpretation of the true causes of conflict, and how they operate.

Yet, I do believe that completely ignoring the potential effect of climatic variations would be a case of "throwing out the baby with the bathwater." The theory and analyses advanced in this dissertation identify specific contexts where droughts can be used to "exogenize" the effect of food on conflict, especially in rainfall-dependent Africa, although in contrast to its conceptualization in extant research, this relationships is negative (i.e., more drought are associated with less conflict). This approach is in line with previous studies that take a similar approach to explaining linkages between economic development and civil war (e.g., Miguel, Satyanath and Sergenti, 2004) or food prices and riots (e.g., Bellemare, 2015), but it fundamentally differs from these studies, in that my analyses associate *abundance*, and not scarcity, with more conflict.

My main contribution in this regard is in drawing a direct linkage between the effect of variations in food availability (due to variations in rainfall) and different types of conflict. Thus, my theory and analyses are in line with the argument advanced by Theisen, Gleditsch, and Buhaug, mentioned in Chapter 1, that "more work needs to be put into the geographical disaggregation of the effects of climate change since these effects will not follow national boundaries," especially considering that "[a]ctors and agency tend to be vaguely portrayed, or outright ignored, in the relevant empirical literature" (2013, 621-622). Indeed, once one follows these guidelines to establish a valid micro-to-macrolevel empirical approach, the findings point, counterintuitively, in the direction of abundance rather than scarcity as a generator of conflict.

Policy Lessons and Broad Implications

The linkages between food and conflict identified here can also assist policymakers to better direct their intervention efforts. First, my insights into armed groups' motivations for fighting in, and indeed over, food abundant areas illuminate a new mechanism through which such violence can be ameliorated: improvements in food distribution within conflict afflicted zones. In this regard, my findings speak to extant studies emphasizing the role of the UN in ameliorating conflict and reducing civilian causalities (see, e.g., Hultman, Kathman and Shannon, 2013), as food aid is often a relevant UN service in such cases. Likewise, my study may also help to identify precisely where within a given country UN forces or other external parties could intervene more generally, so as to most effectively prevent conflict intensifications during periods of relative peace: in food abundant, agricultural areas.

Another relevant insight is that the likelihood of conflict and violence is often influenced by decisions made not only by armed troops, but also by local civilians. Indeed, as was shown in Chapter 3, whether the civilians choose to support their "defenders" or not has a noticeable impact on the probability that raiding groups would attack the region where they live, or even directly attack them. This has important implications for how policymakers might approach violence mitigation in ongoing conflicts, such as the recent civil wars in Syria or Iraq. Agriculture was an important source of income for the Islamic State (Jaafar and Woertz, 2016), which used to rule over large parts of the breadbaskets of the two countries. Indeed, the group maintained agricultural production levels in these regions despite ongoing conflict. IS is notorious for its violence against noncombatants, much of which took place in these regions. Although far from the only explanation for the group's brutality, this dissertation sheds light on some of the causes of violence against civilians in these agricultural areas.

More broadly, with the role of food in conflict gaining widespread attention, it is important for policymakers to understand the nuances of this relationship and avoid categorical claims and pitfalls. This dissertation thus suggests that understanding the role of food in war will change the way both military commanders and peacebuilders approach conflict along three main lines.

First, it is important to bear in mind that throughout history wars and armed conflicts have rarely persisted when and where food was scarce. Napoleon and other great military leaders knew very well that "the army marches on its stomach." Sherman's "March to the Sea" during the American Civil War was designed to starve the Confederate Army into surrender. As was shown in Chapter 4, the British military's strategy of denying food from rebels was crucial to its victories in Kenya (as well as Malaya, see, Ramakrishna, 2002, 140-143) in the 1950s.

As was shown in Chapter 3 and 4, being able to regulate the food supplies available to enemy forces is a powerful strategic tool available to military commanders. Rather than focusing on the fact that countries where food is scarce tend to experience more conflict, policymakers might thus benefit more from focusing on areas within these states where insurgents and, correspondingly, violence tend to concentrate: in food abundant areas. Knowing where food is produced within developing, conflict-afflicted countries, where insurgents and—frequently—state troops are likely to be found, can also point to areas where violence against civilians might be more or less likely if these troops seek to extract"food quotas." This is useful information for international organizations and especially the UN when deciding where to position peacekeeping troops within conflict-afflicted countries.

A second issue is that food scarcities and famines are frequently not the results of natural disasters, but are rather manmade. Nobel Laureate Amartya Sen noted in 1981 that, "starvation is the characteristic of some people not having enough food to eat. It is not the characteristic of there being not enough food to eat" (1981). Sen was referring to the idea that hunger is not always related to food supply; even in places where ample food exists, many people do not have regular access to it. In 2017, four countries were at the risk of experiencing severe famine. Of these, only one, Somalia, experienced prolonged drought. The food security of the others—Nigeria, South Sudan, and Yemen—was disrupted mostly by ongoing violent conflict. War in these countries is destroying crops and cutting off flows of aid and trade, not only reducing supply but also crippling access to food.

This illuminates another problem with focusing on the seemingly linear relationship between scarcity and war discussed in Chapter 1: in many cases this relationship is simultaneous. Scarcity is not necessarily causing violence in many contexts, but rather results from it. Indeed, to this end, the analyses conducted in Chapter 2 showed that once this endogeneity is taken into account, the effect of food on conflict becomes positive rather than negative. While humanitarian efforts and food aid are necessary, they cannot succeed without the "muscle" to back them up. In the absence of military protection by committed nations, such food aid efforts fail to help their intended recipients, and in fact often end up hurting them, as examples from Mogadishu to Yemen soberly illustrate.

Finally, policymakers would benefit from thinking more thoroughly of how the relationships between food and conflict will be affected by current global trends, especially climate change. In the coming decades, environmental degradation, climate change, and population growth will likely reduce food production in some developing countries (Carleton and Hsiang, 2016; Vidal, 2013). This will increase the reliance of armed forces on local food resources and could exacerbate the ill-treatment of civilians during conflict. For example, new behaviors of armed groups might emerge during peacetime, such as a focus on controlling agricultural resource extraction. This may not necessarily be a bad thing. Occasionally, groups that control valuable export crops, such as bananas or sugar, seem to treat local farmers more peacefully (Crost and Felter, 2016). Yet, as was shown in Chapter 3, the peaceful co-option of farmers' labor can turn violent when these groups feel threatened by enemy forces.

A set of strategies that can help in these situations focuses on aiding potential victims of violence before it occurs. Using military forces to halt perpetrators and protect victims on the ground once violence flares is usually very expensive. A lower cost approach could be to assist residents living in these areas escape to safer areas before conflict erupts. Large refugee flows are rightly seen a humanitarian emergency in themselves, but it is a preferred alternative to refugees that become so after surviving violence.

Moreover, helping civilians escape can also weaken violent insurgent groups by draining them of labor required to produce food for consumption and lucrative purposes. As was shown in Chapter 4, without this necessary input, the size of insurgent groups must remain small, and they must spend more time foraging for food or growing it themselves. This allows diverting efforts away from combating well-supported insurgents or preventing human rights abuses once they started, and toward allowing would-be victims to reach safety across international borders and to caring from them once they arrive.

Potential Limitations

A likely objection to the conclusions presented here is that one cannot use historical data to project future trends. The findings presented here might thus not be representative of future rebellions, where scarcity might play an increasingly important role. While these objections have some validity, they ignore technological—such as DNA manipulation and increased reliance on drought-resistant crops—and socioeconomic—such as urbanization and economic development—advances that can mitigate some of these adverse climatic effects. From this perspective, many armed groups will still be forced to continue to rely on locally grown food in the coming decades, and those who enjoy more access to these resources will also be more effective. This claim is at least partly supported by Model 4 in Table 4.6 in Chapter 4, which shows a statistically significant and positive relationship between maize per capita and rebellion over the last five decades, the increasingly noticeable impact of climatic variation notwithstanding.

Another limitation relates to the reliance on local food availability, specifically, rather than food volatility, prices, or alternative routes of obtaining food support. For instance, some rebel groups and militias are able to trade in lucrative natural resources or cash crops such as bananas and coffee (e.g., Crost and Felter, 2016; Jaafar and Woertz, 2016), which allows them to allocate some of these revenues to purchasing food. This is a valid concern, but I believe that it is less relevant for two main reasons. First, as numerous studies have shown (e.g., Koren and Bagozzi, 2016, 2017; Bagozzi, Koren and Mukherjee, 2017), many state and nonstate actors (including militias and rebel groups) are highly unlikely to receive regular support, and must secure food resources in order to sustain themselves. Indeed, I discussed this issue in great detail in Chapter 2. Second, especially in conflict-prone countries, trade routes are likely to be limited or completely eliminated, meaning that the only way to secure food resources is by taking control over "break-basket" territories, as I discussed in detail in Chapter 1. From an empirical perspective, the different models used in Chapters 2, 3, and 4 all control—to some extent—for these alternative pathways, or show that the results are robust to these concerns using different sensitivity analyses. Thus, this dissertation's conclusion that local food access is a crucial variable in understanding the onset, concentration, and duration of both localized conflict and broad rebellion patterns likely holds.

Third, one might argue that the conceptualization of food security along the dimensions of access and availability used in this dissertation does not fully capture several aspects of food security such as refrigerated food, which can increase the amount of food available per capita and food's degree of accessibility to different individuals and groups. Although this is unlikely to affect the robustness of the findings presented here, as the majority of conflicts takes place in countries and regions where little-to-no refrigeration exists, this concern deserves future consideration. Moreover, the increase in land grabbing for the purposes of non-food oriented agricultural resources (e.g., ethanol) or exports production since 2008 (see, e.g., De Schutter, 2011; Crost and Felter, 2016) has potential implications for my findings.

While 2008 is the final year in the vast majority of the analyses conducted above, this remains an important area for future research. Nevertheless, as the different robustness models used in Chapters 2 and 3 clearly show, food and agricultural imports do not substantially diminish the significant effects of localized food production. This suggests that the access to and availability of food resources grown locally play an important role in conflict, which is independent of that of food obtained via other means. Examining the interaction between (the distribution of) food and agricultural imports on the one hand and local food resources on the other, for example, based upon the dependencies of rebel groups or private organizations on these resources or lack thereof, is a potential valuable extension on this study's conclusions, and might uncover important dynamics of violence that the present analysis cannot specifically identify.

Finally, as was stated earlier, the effects of food insecurity on conflict, and indeed conflict in-and-of itself, are the result of complicated interactions between various factors, and primarily between political and economic features (Hendrix and Brinkman, 2013; Buhaug, 2010; Hegre and Sambanis, 2006; Fearon and Laitin, 2003; Collier and Hoeffler, 1998). Hence, while interpreting the present findings as evidence that access to locally grown food resources and food availability shapes local conflict dynamics, this dissertation does not expound on these findings as a complete picture of future socioeconomic developments in this arena, nor does it account for agricultural modifications that might affect or indeed reverse these trends.

Future Directions of Research

Having delineated the different contributions of this dissertation to extant research, and having discussed some of the limitations therein, this final section outlines a future research agenda that builds on this dissertation's findings. The theory and findings presented in this dissertation strongly suggest that scholars should better account for the role of food resources in contemporary analyses of conflict. From a theoretical perspective, as I have argued and shown repeatedly, rebellions involve strong food security-related incentives, as both rebels and—frequently—state forces are forced to rely on locally sourced food. In such contexts, the marginal returns from more food available for each individual trooper are sizable. Unlike other profitable natural resources, food is absolutely necessary for rebellions to succeed. Considering that higher levels of access to staples have positive externalities, such as improving group cohesion and overcoming barriers on collective action, future research into the behavior of rebel groups will benefit from analyzing situations where food matters more or less than other natural resources.

Such studies will also gain from incorporating food access as a proxy of a rebel group's capacity levels, or as a measure of its members' "wealth." Empirically, the effect of food resources on conflict was shown not only to be statistically significant, but also sizable, and substantively comparable to, if not surpassing, that of other benchmark indicators of conflict such as GDP per capita (Fearon and Laitin, 2003). As such, scholars of conflict and political violence more broadly should include food resources-based indicators in models analyzing conflict to verify the robustness of their findings to these issues. As the effect of food resources is at least partly independent of that of economic development, state capacity, or democratization, their viability as a conflict mediator should be taken into consideration.

A second potentially beneficial direction of future research would be to more thoroughly incorporate the role of food prices and food price volatility, which has been the tenet of previous studies (e.g., Bellemare, 2015; Hendrix and Haggard, 2015; Weinberg and Bakker, 2015), with the role of local food availability articulated in this dissertation. Indeed, some studies have already taken the lead on this (e.g., Fjelde and Hultman, 2014; Wischnath and Buhaug, 2014), but I believe more can be gained by using *time-varying* yield data such as the ones used here with food price variations. This can help to explain how global economic factors that affect food prices concatenate with local variations in food production to engender conflict and civilian victimizations.

Another valid direction would be to take a more macrolevel, historical approach to understanding how food security has *historically* affected the frequency of civil war globally. This would help to set the role of food in a more historical context, which arguably predates the effects of climate change. It would also enable scholars to understand how macrolevel variations in food security impacted civil war frequencies globally, rather than within specific countries, considering that some of food insecurity's effects are transnational (Theisen, Gleditsch and Buhaug, 2013).

A closely related factor to food security, and one that has attracted significant attention in the last decade of the 20th century, is "water security" (e.g., Gleick, 1993; Starr, 1991; Amery, 1997). Studies on linkages between water insecurity and conflict have taken a scarcity-based perspective to argue that in countries where water is scarce, actors compete violently over available resources. A fourth direction of research would thus be to incorporate more throughly the role of water security in affecting food security and its effects on conflict. Granted, in the vast majority of cases, the focus on cropland already accounts for the role of water, considering that water is a necessary input for food production. Nevertheless, there are some areas where more high-resolution-data-driven research would benefit from better accounting for the variations in water security. For instance, pasturalist groups tend to live in arid areas, and are therefore forced to rely mostly on livestock—especially cattle—for food support (e.g., Mkutu, 2001; Detges, 2014). For these pastoralist groups, which lead a highly mobile lifestyle, securing access to water is crucial, considering that they livestock needs to drink and eat the grass that grows near water sources. Indeed, violence in these pastoralist contexts frequently arises due to competition over oasis, fountains, and pastureland (Theisen, 2012; Butler and Gates, 2012). From this perspective, future research would benefit from analyzing whether these dynamics resemble those involving crops.

A final substantive direction of future research is in analyzing how food impacts the incidence of other types of violence, especially sexual violence. In this dissertation, I focused mostly on armed conflict and the killings of civilians, while previous studies have focused on atrocities (Koren and Bagozzi, 2017; Bagozzi, Koren and Mukherjee, 2017) and political mobilization (Bellemare, 2015; Hendrix and Haggard, 2015; Weinberg and Bakker, 2015). Recent research associates recruitment mechanisms or group type with a higher risk of sexual violence (e.g., Cohen, 2013; Cohen and Nordås, 2015). It is therefore highly likely that the need to secure resources or to expel civilians from their homes and take control over arable land can motivate armed groups to use sexual violence, either strategically or as a part of other tactics of victimization.

The future research directions outlined here can yield substantive and important findings. Indeed, the analyses conducted in this dissertation illustrate that scholars and policymakers should take the effect of food security and its localized and global impact on conflict and political violence seriously, and give it the same consideration they give other of its important determinants such as economic development, state capacity, and ongoing conflict. In a world where armed groups must rely on local food, and where climate change is inducing more shocks to food production, the detailed theory developed in this dissertation and the vast spectrum of empirical evidence used to support it strongly suggest that we should do more, as scholars, policymakers, and members of the international community, to guarantee that these changes do not jeopardize the human security of billions of individuals worldwide.

Appendix

Proof of Lemma 1

- To derive the first part, begin by comparing the utilities of the civilian producers from providing food support in case the raiders attack, i.e., when $M = 1$ to their utility from not doing so. The utility in the first case is $U_b(M|\theta) = \rho s - \frac{1}{2}\theta^2 - \kappa$. In the second case, the utility of the civilians from conflict is identical, only $\theta = 0$, and so the probability of defender victory ρ collapses to the baseline probability of the defense forces' victory p. The civilians' utility in this case is now $U_b(M|\neg\theta) = ps - \kappa$. Setting the equation such that providing food support is at least as good an option as not providing it gives $U_b(M|\theta) \geq U_b(M|\neg\theta)$, then $p[1 + (1-\delta)\theta\omega]s - \frac{1}{2}\theta^2 - \kappa \geq ps - \kappa$. This can be solved for p such that $p \geq \frac{2\theta}{(1-\delta)\omega s}$. Naturally, from this equation if $\theta = 0$ then it must be true that $p = 0$. Hence, in any case, as long as the raiders are not guaranteed to defeat the defense forces—i.e., $p \leq 1$—the civilian producers will *always* allocate some level of food support θ to their defense forces.

- To derive the second part, assign $\rho = p[1 + (1-\delta)\theta\omega]$ into the civilian producers' utility: $U_b(M) = p[1+(1-\delta)\theta\omega]s - \frac{1}{2}\theta^2 - \kappa$. Taking the derivative of this utility function in respect to θ gives $\frac{\partial U(b)}{\partial \theta} = (1-\delta)\omega ps - \theta = 0$. Isolating θ gives $\theta^* = (1-\delta)\omega ps$.

- To derive the third part, compare the raiders' utility function for attacking a food producing region, i.e., when $M = 1$ and $\delta > 0$ to their utility from not focusing on food producing areas. The utility function in the first case is $U_r(\delta > 0|\theta^*) = [1 - p(1 + (1-\delta)^2\omega^2 ps)](R + s) - \eta$, and in the second case it is $U_r(\delta = 0|\theta^*) = [1 - p(1 + \omega^2 ps)](R + s) - \eta$. Clearly, as long as $\delta \geq 0$, attacking regions with more food production is a preferred strategy for the raiders.

- Now compare the costs of conflict to the utility from not initiating conflict, i.e., when $M = 0$: $U_r(\delta > 0|\theta^*) = [1 - p(1 + (1-\delta)^2\omega^2 ps)](R + s) - \eta \geq 0$, and so $M = 0$: $U_r(M\theta^*) = [1 - p(1 + (1-\delta)^2\omega^2 ps)](R + s) \geq \eta$.

Proof of Proposition 1

To obtain these results take the partial derivative of θ^* in respect to p, ω, and s when $M = 1$.

- In respect to p: $\frac{\partial \theta^*}{\partial p} = s(1-\delta)\omega \geq 0$ because $\delta < 1$; and so θ^* increases with higher probabilities of the defense forces d's victory.

- In respect to ω: $\frac{\partial \theta^*}{\partial \omega} = s(1-\delta)p \geq 0$ because $\delta < 1$; and so θ^* increases when food support is more important for improving the defense forces' overall probability of victory.

- In respect to s, $\frac{\partial \theta^*}{\partial s} = (1-\delta)\omega p \geq 0$ because $\delta < 1$; and so θ^* increases with higher value of land s.

Proof of Proposition 2

- To obtain these results, first take the partial derivative of the raiders' utility when $M = 1$ in respect to δ and compare it to 0 (the utility of the raiders when $M = 0$). Clearly, $\frac{\partial U(r)}{\partial \delta} = 2\omega^2 p^2 s(s+R)(1-\delta) > 0$ because $\delta < 1$; and so the raiders' utility from *initiating* conflict increases the stronger the effect of violence is on reducing food support.

- To obtain the second part of this proposition and show that the raiders will be more likely to initiate conflict if it has a stronger effect on diminishing the defense forces' probability of victory, take the derivative of the raiders' utility from conflict in respect to p to isolate p^*, and then take the derivative of p^* in respect δ. Taking the derivative of $U_r(M|\theta^*)$ in respect to p and isolating p gives $p^* = -\frac{1}{2(d-1)^2 s\omega^2}$, which shows that—unsurprisingly—the utility of the raiders from conflict decreases with higher probability of the defense forces' victory. The derivative in respect to p^* should thus show how the utility from raiding in respect to the probability of the defense forces' victory changes with higher levels of δ: $\frac{\partial p^*}{\partial \delta} = s\omega^2(1-\delta) \geq 0$ because $\delta \leq 1$, and so the raiders will *initiate* conflict even with higher probability of the defense forces' victory if conflict has a strong effect on reducing the food support available to the defense forces.

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